Regional Crop Yield Forecast by Integrated Use of Climate & Crop Models with aid of RS and GIS Techniques

Thesis is submitted to the Andhra University in partial fulfillment of the requirements for the award of

Master of Technology in Remote Sensing and Geographic Information System

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CERTIFICATE

This is to certify that Ms. S.M.Kirthiga has carried out the thesis entitled "**Regional Crop Yield Forecast by Integrated Use of Climate & Crop Models with aid of RS and GIS Techniques**" in partial fulfillment for the award of degree of Master of Technology (M. Tech.) in Remote Sensing and GIS. The thesis has been carried out in Agriculture & Soils Division and is original work of the candidate under the guidance of Dr. N. R. Patel, Scientist/Engineer-SF, Agriculture & Soils at Indian Institute of Remote Sensing, Dehradun, India.

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Dedicated to the agony of people in food crisis……

EVERY GRAIN COUNTS!!!

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ABSTRACT

Ensuring food security ought to be an issue of great importance for a country like India where more than one-third of the population is estimated to be absolutely poor and one–half of all children are malnourished in one way or another. Within season crop production forecasts are widely recognized as an important input in analyzing food balance sheets and anticipating production shortfalls. Though crop production estimation and assessment is done worldwide on a regional extent, advance yield prediction over space and lead-times is less popular especially in India. Limited spread of observatories, lack of infrastructure in the observatories, dynamicity of weather, availability of less efficient process-based approaches to predict the turbulence of weather, heterogeneity in agriculture, lacking in integration of processes, etc pose constraints making it a risky field with not much effective methodology developed till date. In past, the most attempts are made to forecast the crop yield in purely statistical and semi-statistical basis, which proved to be very biased to the location and the year they are developed.

The present study aims at developing a more scientific approach to forecast the crop yield on regional scale and at various time leads within the growing season. An integrated methodology is envisaged to create a coupling system with Agro Informatics tools like Weather model, Crop model and Geomatics. The objective is to develop a robust methodology to forecast the yield at high resolution spatially and temporally with a known level of accuracy. Wheat crop of Punjab and Haryana districts during Rabi season are selected due to its economic significance and homogeneity.

Weather model (WRF) is used to forecast the weather at time scales of seven, fifteen, thirty and forty-five days. The initial conditions of the WRF model is better prescribed with the ingestion of high resolution and updated land surface inputs like land use/land-cover, elevation, and leaf area index. The output from the weather model is coupled with the crop forecast system (DSSAT- CERES Wheat) to forecast the wheat yield at multiple lead-times prior to the harvest of crop. Ancillary inputs are provided spatially and some generalizations in inputs are also made to simplify the methodology. The crop model is implemented on grid basis using GIS. The model is calibrated at point scale (station level) as well as spatially along with sensitivity analysis to establish the approach for the major wheat growing area of wheat i.e. Punjab & Haryana. Yield forecast of wheat obtained both spatially and at station level for representing district. The degree of accuracy and error associated with the forecasts ascertained based on district-level actual crop yields.

The up gradation of the land surface parameters improved the models' performance of simulating temperature by 21%, solar radiation by 18%, precipitation by 5 %, relative humidity by 30%, wind speed by 12% and pressure by 4 %. The forecasts that were generated at multiple time scales had an overall root mean square ranging between 1.58° C to 5.05° C for maximum temperature 1.57° C to 4.14° C for minimum temperature, 3.19 MJm^{-2} to 4.07 MJm^{-2} for solar radiation, 2.3 ms^{-1} to 2.4 ms^{-1} for wind speed, 15% to 20 % for relative humidity and 0.4mm to 0.5mm for precipitation with higher root mean squared error values for the longest forecast. The weather variables that are forecasted showed a good agreement even till 45 days, except for precipitation. The doubling effect of the error is slowly established since the forecast is finished for a less turbulent season. That is, the forecasts are to some extent consistent until 45days since the random behaviour have not started showing up till then. The forecasted yields at point scale were able to capture 95% of variability. There is an increase in the deviation from actual yield as lead time increases, but at forecast times of 30 and 45 days, significant improvement of the yield forecast of about 1 % occurs due to replacement of missing and unrealistic weather variables in the station data. For the regional scenario, the ensemble forecasts of NCEP and WRF are utilized. The forecast at various time scales are combined with the NCEP and forecasts are generated. The forecasts are also good with the ability to capture of about 85% variability of yield on an average. The NCEP with 45 days weather forecast of WRF gave good results spatially with a hit score of about 92%. The WRF forecast showed an average improvement of 30 % over the NCEP data and thus the improvement of yield forecast with the increase in WRF inputs can be explained. The proliferation of error from weather forecast to crop forecast is slow, since the weather forecasts are to some extent consistent. Thus, wheat yield forecast is possible for multiple times (45 days at maximum) in prior with a coupled approach of weather model, crop model and Geomatics for a regional extent at 10km resolution with an average deviation ranging between 5 to 10 %.

Keywords: Crop simulation models, Yield forecast, WRF-ARW model, Weather Forecasting, Ingesting land surface variables, Crop acreage assessment, GIS, Remote Sensing.

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Abbreviations

Abbreviations	Expansion
ARW	Advanced Research WRF
AVHRR	Advanced Very High Resolution Radiometer
DSSAT	Decision Support System for Agrotechnology Transfer
FASAL	Forecasting Agricultural output using Space, Agro-meteorology and Land based observations
GCM	Global Circulation Model
GFS	Global Forecast System
GVF	Green Vegetation Fraction
GMT	Greenwich Mean Time
GRIB	GRIdded Binary
GDD	Growing Degree Day
IMD	India Meteorological Department

IASRI	Indian Agricultural Statistics Research Institute
ISMR	Indian Summer Monsoon Rainfall
LSM	Land Surface Model
LAI	Leaf Area Index
LUT	Look Up Table
MODIS	MODerate resolutuion Imaging Spectroradiometer
NCEP	National Centers for Environmental Predictions
NDVI	Normalized Difference Vegetative Index
RCM	Regional Climate Model
SPAC	Soil-Plant-Atmosphere Continuum
WRF	Weather Research and Forecasting
WOFOST	World Food Studies

Chapter 1

INTRODUCTION

1.1. Motivation

"The quest for food security can be the common thread that links the different challenges we face and helps build a sustainable future"

Jose Graziano da Silva, FAO Director - General

Ensuring food security ought to be an issue of great importance for a country like India where more than one-third of the population is estimated to be absolutely poor and one–half of all children are malnourished in one way or another *(Dev, S.M and Sharma, A.N., 2010).* Moreover problems like expanding population, climate fluctuations and constraints in the availability of resources no way exaggerates the urgent need in changing our perspectives on Agriculture more than just a driver of the country's economy. There is a call for efficient management eliminating the gaps between different elements in the agricultural supply chain. Seeing that our resources are limited we are in a condition where we have to rise with these limited resources and thus preciseness is required at every level of the activity. Especially for India, which is much diversified in cropping pattern, irrigation level, soil fertility, etc, it's hard to do strategic planning without some kind of decision support system that links across fields relating farms to policy makers. With the technology boom, Remote Sensing and GIS, Process-based weather models, Crop and Soil Models, Market intelligent systems, Data Mining is becoming popular in the field of Indian Agriculture; one can spot the increase in the level of quality inputs in dimensions of both time and space to the agricultural activities.

1.2. Need for the Research

Crop production forecasts are widely recognized as an important input in analyzing food balance sheets and anticipating production shortfalls *(Jayne, T.S and Rashid, S., 2010).* California growers used the 2004 forecast of a large rice harvest to arrange greater storage capacity, and used a 2005 forecast of reduced almond production to allocate limited quotas among preferred customers. Accurate early warning of crop failures can go a long way in mitigating the undesirable effects like price rise and agrarian distress through public policy. Thus, forecasting the condition of the crop specific variables at multiple lead times within season would serve different people in different ways from addressing food security knowing the projected yield to the stabilizing of country's economy with well-planned mitigation strategies and trade policies. The *18th session of the Asia and Pacific Commission on Agricultural Statistics, 2000* addressed this specific issue as "*Crop Forecasts should be timely, reliable and with known level of precision. Useful crop forecasts should be made soon after planting, during growing season and some weeks before harvesting. Methodologies for forecasting yield should be strengthened to enhance utility of production forecasts*."

1.3. Description

1.3.1. Crop Yield Forecasting – An Overview

Crop yield forecasting is a research question that dates back more than a century in 1860's *(Spinks, G.R., 1956)* till recent times, yet the question stands half-way resolved with hope of a best solution in times to come. Lot of techniques are available to forecast the crop yield *(Murthy, V.R.K., 2003)*. To state a few techniques the judgemental forecasting, statistical forecasting, semi-empirical forecasting using sophisticated crop-weather relationships, process based crop simulation models and coupled climate-crop models. Each of the techniques has its own advantages and drawbacks. Some of the major methods that are in use in the present day and the limitations that one will encounter while using each method is documented in the literature review.

Our interest is process-based simulation models. These simulation models form a group of models that is designed for the purpose of imitating the behaviour of a system. They are mechanistic and in the majority of cases they are deterministic. Since they are designed to mimic the system at short time intervals (daily time-step), the aspect of variability related to daily change in weather and soil conditions is integrated. Thus it addresses the Soil-Plant-Atmosphere continuum (SPAC) which is vital function of plant growth. They have the ability to mimic relevant physical, chemical or biological processes and to describe how and why a particular response results. Thus, these models usually offer the possibility of specifying management options and they can be used to investigate a wide range of management strategies at low costs at various scales ranging from point to spatial scales. Most crop models that are used to forecast crop yield fall within this category. Ample state-of-art process based simulation models has been developed *(Jones et al., 1984; Tsuji et al., 1994; Supit et al., 1994)* and validated for crop production forecasting world-wide. The simulation for short time-step demands a large amount of input data (climate parameters, soil characteristics and crop parameters) be available for the model to run which confines the usage of these models.

According to Armstrong, "*judgement pervades all aspects of forecasting*", which is close to the following definition of crop yield forecasting: "*the art of identifying the factors that determine the spatial and inter-annual variability of crop yields*". It is an "*art*" that the same inputs given to different forecasters, the results obtained would vary from better to best or even worse to worst depending on the strategic approaches that they use. Thus a strategic integrated approach of coupling two or more techniques brings these approaches in one platform were the problems associated with one are offset by the benefits of the other. "*In combining the results of methods, one can obtain a result whose probability law of error will be more rapidly decreasing*" (*Laplace,1818).* Often it is not possible to include all the variables in a single model. In such situations composite forecast can be obtained as a suitable combination of forecasts obtained from different models. Various strategies for combining forecasts have been suggested under different situations *(Mehta et al., 2000).*

1.3.2. Some of the similar efforts that went popular

Considerable efforts on realizing the above mentioned objective has been done world-wide. The US Department of Agriculture (USDA) first published a review on the combined use of agro-meteorological models and remotely sensed data (*Wiegand et al., 1986*). *Masutomi, 2013* demonstrated the integration of crop and climate models with a coupled model MIROCrop-paddy that he developed himself to study the climate effects on rice production coupling a climate model and crop model. *Horie et al., 1992* showed an example where the crop models, regional weather databases and historical yield data is used to forecast rice yields for different regions of Japan.

Early warning systems on expected crop production are issued by every country at different lead times world-wide combining different approaches (*Agricultural Monitoring Meeting convened for the Integrated Global Observations for Land (IGOL), 2006*).

One similar approach of integrating various approaches for the crop production forecasting in India is the official forecasts (advance estimates) of major cereal and commercial crops that are issued by Directorate of Economics and Statistics under FASAL (Forecasting Agricultural output using Space, Agro-meteorology and Land based observations) scheme operational since Aug. 2006. It follows a methodology that provides multiple forecasts for rice and wheat using remotely sensed data for acreage forecast whereas forecasts for productivity are obtained using meteorological and agro - meteorological indices *(Patel et al., 2004).* Now these district-wise forecasts are extended to crops like cotton, mustard, sorghum and sugarcane. Certain critics on this scheme stated that the methodology used in the scheme is a practical approach of crop yield forecasting though it does not explain a "cause and effect" relationship *(Baier, 1977)*. Thus there is still a scope to improve the production forecasts from a methodology that includes more scientifically strong, process based models to represent the weather than just statistical relationships that symbolize the climatology.

1.3.3. Limitations with present methodologies

Crop simulation models with no doubt could provide scope of improving crop yield forecasting since they are scientifically sound, integrative in nature and considers enormous number of variables that affects the crop growth. They simulate seasonal profiles of LAI, which is of main importance as it drives absorption of solar radiation and evapo-transpiration, and thus carbon assimilation. However, canopy development and allocation of daily assimilates to leaves are described through empirical relationships. The use of inaccurate coefficients within a relation affecting canopy development may lead to important errors on the estimation of biomass production (*Porter 1984*). Weather has a demonstrated effect on crop growth and development. Through years from the advent of crop forecasting, the effect of weather has been considered directly or indirectly. In crop simulation models especially the most important relations between weather and crop growth are quantified and thus weather parameters serves as important driving variables for crop growth and allocation processes in-built within these crop models *(Hoogenboom, 2000)*. Thus there is a necessity to represent these weather inputs in an appropriate manner. The crop forecast can be made in advance with crop models if weather information for forecast period is represented either by long-term weather or weather forecasts suitably. Among all the inputs, the weather variables are very dynamic while the others are more or less static to some extent. If one is able capture this dynamic nature of the weather then transferring that dynamicity into the crop development can be done with ease by crop simulation model. Presently in most of the researches carried out in India and abroad, the weather is forecasted using empirical and semi-empirical approach. They tend to capture trend existing between years. These approaches are made of the assumption that the present year weather is a part of the composite population of the previous years. This is not convincing to be applied to crop model, since crop growth depends more on the distribution of weather within a season than on season averages from previous years. Also the weather is regressed from historical station data. The availability of quality data is a question; even if it is available the problem is that the weather station distribution coincides with important regional population centres rather than being distributed geographically to coincide with the crop acreage. Furthermore it represents single point data while crop yield at point basis with a sparse spread is hollow when interest is fully on regional estimation.

Very limited research is being done for using weather forecast by dynamic means in crop simulation models. Most of the models that combine crop and climate models are for the purpose of climate impact study. The use of process based models that capture the interaction between the land surface, atmosphere and ocean would definitely help to improve the forecasts. Constrains that existed in using the atmospheric-ocean coupled models had been their coarser resolution thus causing a mismatch of the scales that the crop model simulates the crop and the processing capacity required to do it. Development of regional models and the high processing capacity of ordinary systems open up a new sphere to explore converting these meaningful weather forecasts to applied crop yield forecast. *Bryan. C. Weare, 1990* had a vision that numerical weather models would be apt for multi temporal crop prediction. A fact that is supported with a large number of studies is that enhanced representations of land surface conditions would definitely improve the forecast skill of the model. But using this actuality for practical utility of providing improved forecasts is not given much attention expect for a few paper published in this regard.

Moreover, very few studies have exemplified use of the crop simulation models in geospatial domain for regional crop forecasting. The main reason behind this is the unavailability of spatially explicit and dynamic weather information at reasonably good resolution in last century. But now with improvement in regional weather modelling, weather input could be generated at spatial and temporal scales that are mostly comparable with the scale that the crop simulation model simulates the crop growth and development. Also the other critical inputs like crop acreage, soil status, management and genetic characteristics could be derived from remote sensing or associated with the data collected from various sources with the help of geospatial techniques in spatial coverage.

1.3.4. Project in a nutshell

The crop model – Decision Support System for Agro-technology Transfer (DSSAT) is one of the oldest and finest among the crop models that simulate the crop growth with requirement of basic inputs like daily weather, crop genetics, initial soil conditions and management practices. As mentioned earlier, the weather inputs are very critical to DSSAT as the model simulates the crop growth on daily basis accumulating the biomass as a function of growing degree days .The model can forecast the future condition of the crop given the future condition of weather, as the other inputs are to be mentioned only once while daily defining of the weather is required for a minimal run.

In Indian scenario, the analysis of existing data indicates that at least 50% of the variability of crop yields is related to weather and the uncertainty in the advance estimates of crop production can be reduced substantially by suitable adjustments through timely and accurate weather forecasts. Thus the weather input criticality is treated with the use of the illustrious dynamic numerical weather model Weather Research and Forecasting – Advanced Research WRF (WRF-ARW) to forecast the weather at different time scales at a resolution of 10 km. The generated multi-scale forecasts are input into the crop model to visualize its effects on yield forecasting at a semi-optimal crop condition.

During the process knowledge of remote sensing and geospatial techniques is utilized at all the stages to achieve forecast on a regional scale. The landuse-landcover, leaf area index and terrain information obtained from the earth observation satellites are ingested into the WRF model to improve the representation of initial conditions of the land surface parameters and thus enhancing the forecast skill of the weather model. Also the crop acreage, sowing dates are obtained in a spatial extent from the RS & GIS techniques. The other vital input to the crop model is soil initial condition prepared with help of geo-informatics over a spatial extent. The MODIS LAI is used to calibrate and validate the model spatially. The DSSAT is run in a spatial context to address the crop yield forecasting in a region wide manner at high spatial and temporal resolutions.

The project demonstrates its utility for wheat crop covering Punjab and Haryana as a whole since it accounts to nearly 31.77% share of the country's wheat production and ranks first in productivity of the same *(Economic Survey, 2011-12)*.

1.4. Scope of the Investigate

The project seeks to derive a decision support system for early warning of wheat yield and production information at high spatial and temporal resolution. The project tries to overcome the limitations stated in Section 1.3.3 with an improved composite approach. The numerical weather model forecasts the weather and gives specific parameters at a lead time of seven days, fifteen days, thirty days and forty five days. These inputs are then provided to the crop model with ancillary inputs prepared from geospatial and remote sensing techniques. Thus this project also aims at developing a platform were three high end technology i.e. crop model, climate model and geomatics intermingle to give a improved forecast of crop yield in regional extent at district level and at various lead-times.

Certain simplifications are assumed in the project that the crop is under semi-optimal conditions i.e. the management, crop cultivar, fertilizer and irrigation are in the optimal conditions while the soil initial conditions and weather components vary.

1.5. Benefits of the Research

The potential benefit of the project is that it is cost effective and can offer rapid multiplicity of decisions with different lead times at specified accuracies. The regional spread of the decision makes it more valuable and central for application in real time. It also opens up a new prospect for the researches to combine numerical models with crop models for real time crop forecasting than only for climate studies. This investigate presently just in research mode to develop a robust methodology has all the qualities of becoming a full-fledged project national/ regional level with little more probing into its limitations and accounting for it.

1.6. Distinctiveness of the Study

It is one of the early studies that combine numerical weather models to crop model for the purpose of regional crop yield forecasting. It is moreover the first study to use global utility of WRF to forecast weather with help of improved representation of land surface parameters obtained from earth resource satellites. It is also one of its kinds that aim at improving methodology for operational regional crop forecasts at various lead times. This kind of study of combining three spheres in one platform is unique in the researches of recent times. The study moreover models the dual feedback mechanism existing between land and atmosphere by the climate and crop models which is one of the interesting research areas currently, i.e. the feedback land surface vegetative parameters provide to atmospheric modeling in terms of fluxes, atmospheric boundary layer, entrainment, etc., and also the feedback the atmospheric weather forecasts gives to crop model in terms of photosynthesis, assimilation, evapo transpiration, etc., to simulate the crop yield.

1.7. Research Questions

The study is basically designed with these research questions in mind:

- Can ingestion of remote sensing derived land parameters into climate model yield satisfactory improvements weather parameters?
- How efficient is the input of forecasted weather data from regional climate model to predict within-season wheat crop yield?
- Is it possible to make multiple crop forecasts with improved accuracies by combination of climate and crop model?
- What is the degree of regional appeal that the output could hold by integrating remote sensing and geospatial techniques into the approach?

1.8. Research Objectives

Finally the study could stand to solve the following objectives:

- To generate reasonably forecasted weather inputs at different lead-times by ingesting remote sensing derived land parameters to regional weather model.
- To test applicability of coupling climate model and crop model to forecast yield at different time scales.
- Multiple yield forecasts and their inter-comparison with actual crop yield of wheat at regional level.

1.9. Structure of the Thesis

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

Chapter 2

REVIEW OF LITERATURE

Agriculture is an essential component of societal well-being, and agricultural production influences and is influenced by health, water, ecosystems, biodiversity, the economy, energy use and supply. Large scale changes are taking place in the distribution of agricultural lands and crop production. International trade, national agricultural policies, commodity prices, and producer decisions are all shaped by information about crop production and demand. Thus, forecasting the production level within season if well-organized would serve a number of purposes like storage, distribution, pricing, marketing, import- export, etc. thus enhancing the quality of decisions taken at every level. However, crop yield forecasting in regional level is not a simple task. Value of crop production forecasts is very high when they are reliable and timely. In order to give a quality output there is a need to combine techniques. It is a challenging field that it has been attracting a number of research works. Several pioneer works has been published that motivates and supports several aspects of the thesis. This section is a compilation of such research works.

2.1. Crop Yield Forecasting

On field surveying or so called judgemental forecasting systems is the earliest method of forecasting crop yields. This approach that uses sampling techniques at field level with inputs from farmers and extension workers could give better results but they can be more subjective and far from being time and cost effective *(for instance the "Delphi expert forecasting method" for coffee, Moricochi et al., 1995)*. There is a need to develop sound objective forecasts of crop production. The main advantage of those developed models would be to provide objective forecasts of regional yields in advance of the harvest proper, and at the fraction of the cost of sampling techniques.

Through common sense one can infer the importance of weather on crop growth and yield. Plenty of research has been done to examine the impact of weather parameters on the crop growth and phenology *(Baier, W., 1977; Agrawal et al., 1980).* Most of the techniques developed to forecast crop production validate this concept. Traditional statistical techniques are purely empirical being uni-variate or multi-variate. They relate crop yield either to the crop components that affect yield or consider the crop-weather relationships by developing statistical relationships between historical data. These models require a long series of weather data and reliable crop yield data for calibration of the model. The data of one station is then used for large areas, which may not be representative of regional variability in weather conditions. Indian scenario has also seen such kind of models successfully used for forecasting yields of various crops at district level and agro climatic zone level *(Agrawal et al, 1980; 1983, 2001; Jain et al 1985; Mehta, et al. 2000)*. Some more sophisticated techniques also came as an improvement to the simple empirical models like complex polynomial approach, artificial neural network approach, semi-empirical approach, etc, were also tested in recent years (Mehta et al., 2000). Most models do not respond well to extreme conditions in weather. The major disadvantage is that they work best when the weather conditions are within the range of the data that are used for fitting the models. While these methods may result in accurate predictions, they typically lack the interpretability of process-based models *(Barnett, 2004).* These models are known to often over-react due to their dependence on a too limited number of factors *(Gommes, 1998).* The data available for this purpose are often insufficient. A practical problem is also scarcity of availability of key weather parameters driving the processes of crop growth and development (e.g. Temperature, Sunshine hours and Relative humidity etc.)

A few techniques also valued the importance of plant characteristics (biometrics) on yield *(Vogel, 1985).* Effects of weather and inputs on crop performance are manifested through crop stand, number of tillers, leaf area, and number of earheads etc. which ultimately determine crop yield. As such, plant characters can be taken as the integrated effects of various weather parameters and crop inputs. In India, yield is directly regressed on plant counts and yield contributing characters for obtaining forecast model. Considerable work has been done at Indian Agricultural Statistics Research Institute (IASRI) using this approach *(Jain et al. 1985, Chandrahas et al. 1989)*. The data are collected at different periodic intervals through suitable sampling design for 3 to 4 years from farmers' fields. This technique is however not applicable in varieties that takes short interval to complete critical stages for example a country like India were the interval between the grain formation and harvest is less than even one month.

Another popular approach in regional crop yield estimation is the use of Remote sensing data to demarcate the cropped area spatially; to identify the present vigor of the crop by certain indices and relate it to final yield. The primary assumption is that the spectral data has a strong correlation with canopy parameters. Several studies established good correlation between vegetation indices and grain yield *(Tucker et al., 1983; Malingreau et al., 1986; Goward et al., 1987; Doraiswamy et al., 2001)*. In India the research at a larger scale started with Crop Acreage and Production Estimation (CAPE, 1987) mission under the Remote Sensing Applications Mission by Department of Agriculture and Cooperation and Department of Space for state-level crop estimates. Such spectral based yield models also subject to uncertainty due to lack of accountability of abnormal weather conditions. Also the presence of clouds in the data increases the complexity in acquiring data at different time intervals which is essential to develop a robust model.

2.2. Crop Simulation Models for Forecasting Crop Yield

The previous section summarises the evolution of crop yield forecasting stating the available methods, its advantages and loop holes. It also helps one to understand the advantage of using crop simulation models as an underpinning method over the other existing methods. This section compiles the past and present usage of the crop models, thus supporting the idea of using crop simulation models.

2.2.1. Simulating Crop Growth and Yield by Deterministic Crop Simulation Models

The early life stage began with the dawn of crop models more than thirty five years ago with the introduction of the mainframe computer in the 1960s. Past fifteen years has seen a wide usage of crop models in the field of production forecasting, especially with the advancement in the processing capacity available and the knowledge of computers. The reason behind this is that most of the simulation models are programmed to computer based applications. *De Wit* carried out the first attempt to model the photosynthetic rate of crop canopies (*De wit, 1965*). From then ample of crop models evolved. Dynamic growth simulation models are reported to have universal applicability compared with statistical models which are largely site- specific *(Jamieson et al., 1991).* Empirical models are often described as black box models while mechanistic models attempt to describe internal processes (*Addiscott, 1993*). Crop simulation models are the most accurate and most versatile in that they attempt to describe the crops behaviour as a function of the environmental conditions *(Gommes, 1998). Buck-Sorlin, 2002; Tardieu, 2003; Yin and Vanlaar, 2005;* collectively acknowledged the utility of the crop simulation models in crop management and also suggested that the efficient use of these models has the ability to play a key role in second green revolution.

Copious efforts to review, compare, test, calibrate and validate these models at different environments have been part of research. An outstanding inventory and review of the then existing crop simulation models were done by *Plentinger and Penning de Vries, 1995. Nayamuth, 1999* reviewed the number of available paper that addresses crop simulation modelling and tabulated some of the popular crop models with their basic function till then. *Amjed et al., 2012* attempted to review the crop models, its usability and dependability. They also added that use of crop models would give quick and suitable solutions when compared to the traditional methods.

Efforts were made to assess the model's efficiency separately and in comparison with one another to help increase the fidelity associated with each model. *Tom Hodges (University of Missouri), S.K. Leduc (NOAA/NESDIS) and A. Eddy (Oklahom Climate Survey)* used the CERES-Maize model to forecast yields during the 1983 drought. The researchers used actual weather conditions up to July 1, but simulated the weather for the remainder of the growing season based on historical data. The model was run at 51 first order stations in 14 Midwestern states. *Asseng et al., 1998*, assessed the crop model APSIM (Agricultural Production Systems Simulator) for its effectiveness in simulating crop yield, drainage and NO_3 leaching for Western Australia. They recorded their findings that Crop growth and N uptake were closely predicted up to anthesis, but a poor fit between observed and predicted crop growth and N uptake was noted postanthesis. Usefulness of WOFOST (World Food Studies) simulation model to predict maize yield gaps on the eastern slopes of Mt Kenya was tested by *Mureithi et al., 2003.* They concluded that potential and water-limited grain yield of maize obtained via the application of WOFOST model compared relatively well with the yield obtained from the experimental plots. *Biernath et al., 2011,* evaluated the ability of four different crop models (SPASS, CERES-Wheat, SUCROS and GECROS) to predict different environmental impacts on spring wheat and made some important conclusions on the shortcomings of the underlying processes in all of the models.

2.2.2. DSSAT for Crop Production Estimates

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

2.2.3. CERES Wheat for Wheat Simulations across Globe

CERES was developed for agricultural practice to simulate crop development and grain yield (*Ritchie and Godwin, 1987; Ritchie et al., 1987*). The model was designed for use under extremely different environments, including those with limited water availability (*Otter-Nacke et al., 1986; Otter-Nacke and Ritchie, 1989*). *Biernath et al., 2011,* concluded after comparing between four simulation models, if only yield and total aboveground biomass are considered, the CERES simulations were of high quality, and the model can therefore be recommended for up-scaling yield and total above ground biomass at regional levels and in climate change studies.

Numerous studies in Indian –context and worldwide revealed the adaptability of the model in predicting the wheat yield in several soil and climatic conditions. *Fei, Qing-Pei and Ripley, 1985* used the CERES-Wheat model in southern Saskatchewan as an operational tool to predict yields. They initially tested the model with 25 years of historical data from the Saskatoon crop district.

After correcting for a "technology trend" of 32 Kg/ha per year, they found that the CERES model was capable of simulating yields for 1960-84 with a correlation coefficient of 0.70. *Hundal, S. S., Kaur, P, 1997* evaluated CERES-Wheat to simulate plant growth and yield in areas of Punjab, India. The results obtained with the model for the eight crop seasons showed satisfactory predictions of phenology, growth and yield of wheat. However, the biomass simulations indicated the need for further examination of the factors controlling the partitioning of photosynthates during crop growth. The results of this study reveal that the calibrated CERES–Wheat model can be used for the prediction of wheat growth and yield in the central irrigated plains of the Indian Punjab. The CERES Wheat model was validated for 13 representative locations in the main winter wheat producing regions in China to examine its suitability to model winter wheat production, using the agronomic, soil and daily weather data collected from each site concerned, by *Jiang Min et al., 2003*. They suggested that the model's results were productive expect for places with extremities in rainfall. *Alexandrov et al., 2001* briefed the applications using crop simulation models in Austria and Bulgaria. They had discussed on a specific application using CERES-Wheat in Austria winter wheat productivity. The simulated grain yields are in most cases in accord with the measured data, with predicted yield results mainly within acceptable limits of ±17 % of measured yields. Another attempt by *Xian Wang et al., 2008* to use CERES Wheat model for predicting the wheat yield in Beijing, China was made. The results of this study were positive and encouraged CERES-Wheat to be used for similar kind of studies.

2.2.4. Defining the limits of Crop Simulators

Though plentiful papers accredited the use of crop simulation models DSSAT-CERES-Wheat in specific, some of the papers critically state the limitation boundary of these models. Few crucial points that have to be considered while using crop models for yield simulations are listed in this section.

The 'School of De Wit' *(de Wit and Goudriaan, 1974; Bouman et al., 1996)* defines four levels with respect to the evolution of the crop growth simulators *(Penning de Vries and van Laar, 1982; Penning de Vries et al., 1989).* The levels were to denote the complexity at which the model operates. The Level1 models uses temperature and solar radiation to simulate growth and development and to calculate potential production. While Level 2 includes precipitation and irrigation as additional inputs for simulating soil and plant water balances. In Level 3, soil nitrogen is added as an input to simulate soil and plant nitrogen balance in addition. Level 4 is advanced stage where soil minerals are also added along with pests, diseases and weed. The complete soil-plant-atmosphere system is simulated. At present we are in a transition period between level 3 and level 4. Input requirement of most of the models at present substantiate this point. Thus we are in a stage where process are not fully understood either fully ignored. The *technical documentation of CERES-Wheat Ritchie and Godwin, 1991-199*8 documented the limitations in the development of methods to simulate the actual process. The development of the growth routine in conjunction with the rest of the model has been a major challenge in developing this model because the partitioning of assimilate is a dynamic process, requiring several feedback mechanisms. A major difficulty associated with verifying an intercepted radiation-biomass production relationship has been the lack of knowledge concerning the fraction of assimilates partitioned to the roots. Although several investigations were made to establish this relationship for use in CERES-Wheat by measuring roots or by approximating their weights compared to above ground biomass, there still remains considerable uncertainty in calculating the fraction of assimilate partitioned to the roots and tops. Also, the mechanisms of grain number determinations were not fully understood until now which is commonly agreed by *Fischer, 2008; Sinclair and Jamieson, 2006*. *Biernath et al., 2011,* after inter-comparison between models stated that major weakness of CERES is the simple model of light absorption that does not consider diffuse and scattered light. As a consequence, biomass production was overestimated during the juvenile phase. They also documented this was due to low parameterization effect in certain methods used by CERES-Wheat. The same group accepted that over-parameterization of another model also lead to unfavorable results. Thus models should be made simple, but not simpler. These problems with the methods and the parameterizations used in the model should be considered by model developers to manage the uncertainties associated with the crop simulation models.

Another aspect of limitation is with the uncertainties tied with input data. For rigorous use of these models for crop management decision in a given area, more carefully derived input environmental parameters are important *(Kiniry et al., 1991). Aggarwal, 1995,* quantified the impact of uncertainty in inputs with the various simulated parameters of the model WTGROWS. The Monte Carlo simulation technique was used to analyze total uncertainty. The results showed that uncertainties in crop, soil and weather inputs resulted in uncertainty in simulated grain yield, ET and N uptake, which varied depending upon the production environment from potential to stressed condition. There was an 80% probability that the bias in the deterministic model outputs was always less than 10% in potential and irrigated production systems. In rainfed environments this bias was larger. He also stated that uncertainties are associated with weather variables since there might be some random errors and the systematic measurement errors. The missing weather data, the acceptance of direct face value from recorded data and the distance of the weather stations from the actual field pose a serious problem for simulating crop. If case of prediction, the unavailability of a robust method for predicting the future weather at daily time-step comes as another issue in the usage of the model. *Nonhebel, 1994,* has reported that simulated wheat yield was overestimated under potential conditions and underestimated under water-limiting conditions when generated meteorological data were used with SUCROS87. The uncertainty in other variables like soil initial condition, crop cultivar description in terms of genetic coefficients and management information has also got considerable effects on the yield simulation which was validated by *Bouman, 1994*. It is common in cropping systems to have large volumes of data relating to the above-ground crop growth and development, but data relating to root growth and soil characteristics are generally not as extensive. Using approximations may lead to erroneous results. Large variations in wheat yields (4.5 to 8.0 t ha^{-1}) attributable to within-field soil heterogeneity were reported by *Russell and Van Gardingen, 1996*. Hence, the use of average values of soil characteristics as model inputs could lead to some errors in simulated output.

Gommes, 1998, explained that these simulation models are often not able to forecast the yield increase or drop due to a period of dry and sunny weather at unusual times of the crop cycle. He also explained that the models performance is not appreciable at times of extremities. *Nayamuth, 1999,* made clear that when a model is applied in a new situation, the calibration and validation steps are crucial for correct simulations. The need for model verification arises because all processes are not fully understood and even the best mechanistic model still contains some empirism making parameter adjustments vital in a new situation.

One more concern is the application of the outputs from the simulation models –Spatial Sense. *Moulin and Guerief, 1999,* listed the serious issues in extrapolating the crop yield simulation from farm level to regional level. Though the models have a good predictive ability, their usefulness has been restricted to applicability at research plot scale due to high input data requirements. Their implementation at the scales of farmers' fields, district and province is restricted by the input data availability at corresponding scales. Desired accuracy is not also attained due to averaged input conditions (*Russell and Van Gardingen, 1996).*

2.3. Weather and Crop Models

"All agriculture (and hence human survival) is dependant upon the weather." Thus quantifying the effects of weather parameters in the crop simulation is unavoidable. This section consists of evidences that lead to the realization of the importance in inputting quality weather inputs and developing refined techniques for generating such weather inputs.

2.3.1. Understanding the linkage between Weather and Agriculture

Weather is a key factor to control the crop growth and thus production. *Hoogenboom., 2000* gave an excellent briefing of the relationship that existed between weather and crop by pilling up the literatures that proved the impacts of the former on the later. He stated that of all the weather variables the critical ones are air temperature, solar radiation and precipitation.

Hodges, 1991 in his study concluded that air temperature is a main weather variable regulating the rate of vegetative and reproductive development. He also added that in most cases, an increase in the developmental rates as temperature increases, while after a threshold the reverse occurs. Thus a non-linear relationship exists. Temperature is a vital variable for some important stages in the crop's life cycle. Stress in either forms i.e. very low temperatures or very high temperatures than the optimum range for each crop causes dormancy or reduction in crop duration leading to high variation in the final output. Temperature is an important environmental factor influencing the growth and development of crop plants. Influence of temperature on phenology and yield of crop plants can be studied under field condition through accumulated heat units system was acknowledged by *Bishnoi et al., 1995. Monteith, 1977* confirmed that cumulative seasonal light interception for several crops grown with adequate soil water supply was closely related to biomass production. Although the calculated relationship for the different crops had different intercepts, there was considerable similarity. Radiation values were for those wavelengths in the photosynthetically active range and were assumed to be 50 percent of the solar radiation. *Hesketh and Baker, 1967* showed that the net photosynthesis rates of maize and cotton canopies, measured over 15 minute periods, had a nearly linear relationship to light interception. The field studies of *Spiertz and van de Haar, 1978*, and *Puckridge and Rathowsky, 1971* verified the efficiency of conversion of intercepted radiation to biomass is greater during periods of low radiation than during periods of high radiation. *Boote and Loomis, 1991* also added to this fact that solar radiation provides the energy for the processes that drive photosynthesis, affecting carbohydrate partitioning and biomass growth of the individual plant components. Photosynthesis is normally represented through an asymptotic response function, with a linear response at low light levels. Basically, air temperature and global radiation determine the potential production, and precipitation determines the extent to which this production is actually reached, *Nonhebel, 1994. Hoogenboom, 2000* explained the importance of precipitation. Precipitation does not directly control any of the plant processes. It is considered to be a modifier, which indirectly affects many of the plant growth and developmental processes. Drought occurs during periods of insufficient rainfall, while water logging occurs during periods of extensive rainfall. According to *Ibarra and Hewitt, 1999* the majority of crop failures in the United States are associated with either a lack of or an excess of rainfall. High temperature, humidity, and rainfall can create a favourable environment for fungal diseases *(Fraisse et al., 2006). Hoogenboom, 2000* also added up few other factors of weather that affect crop productivity like soil temperature, wind, relative humidity and if mentioned can improve the model's performance.

2.3.2. Criticality of Weather Variables in DSSAT- CERES Wheat

It is obvious that the processes discussed above should be included in the model to simulate the crop growth in a realistic mode. Ritchie et al., 1998 mentioned that the objective of many crop models is to predict the timing and growth rate, the partitioning of assimilates into economic yield components and to compute the supplies of essential resources (water and nitrogen). A universal backbone of such models is the relation between air temperature and phasic development. Heat units expressed in growing degree - days serves as input to describe plant ontogenetic development which may be modulated by photoperiodism and vernalizations requirements. *Hoogenboom, 2000* also confirmed this in his paper that one of the main goals of crop simulation models is to estimate agricultural production as a function of weather and soil conditions as well as crop management. The weather variables discussed previously, such as air temperature, precipitation, and solar radiation, are, therefore, key input variables for the simulation models. It is defined as primary weather input variables and the other input variables, including wind speed, relative humidity or dewpoint temperature, open pan evaporation, and soil temperature, as secondary weather input variables.

Godwin et al., 1990 elucidated that in CERES-Wheat this relationship is completely quantified with empirical relationships. There are in total nine stages of wheat as represented in CERES-Wheat. Temperature is valued for its non-linear effect on crop growth. Temperature has a maximum influence during germination, vernalization stages with normal effect in other stages. Winter wheat varieties usually require exposure to relatively low temperatures before spikelet formation can begin. This low temperature requirement for flowering, called vernalization begins at germination. This is very critical to wheat crop development. At this stage a temperature low of 0° to 7° C is required for atleast 50 days. The thermal development units are the unit required for completion of each stage, is a function of daily temperature and diurnal variation. Two factors can reduce potential biomass production: non-optimal temperatures and water stress. A weighted daytime temperature is calculated from the minimum and maximum daytime temperatures for use in the photosynthesis temperature reduction factor, where the optimum daytime temperature is considered to be 18° C. Also calculation of potential evaporation requires an approximation of daytime temperature. Solar radiation is a critical parameter to the crop model. It has a maximum influence in the photoperiod sensitivity of wheat crop soon after vernalization. A photoperiod of atleast 20 hours per day is required; otherwise there is a delay in the phasic development. Also potential biomass is given as a function of intercepted photosynthetically active radiation. Rainfall is a factor used to calculate the daily water stress or runoff if excess, thus influencing the evapo-transpiration managing the water balance along with the irrigation schedules. Relative humidity, soil temperature and wind speed are in major used to calculate evapo-transpiration in Penman method while it is optional when using Priestly-Taylor method.

2.4. Extended Range Forecasting of Weather

Ample efforts are taken world-wide for forecasting the weather in extended time scale, world-wide. The United Kingdom Meteorological Office produces deterministic and probabilistic forecasts from 30-day ensembles operationally every other week, while the Japan Meteorological Agency runs weekly operational 30-day forecasts. The National Centers for Environmental Predictions (NCEP) performed several 30-day dynamical forecasts at 24-h intervals from December 1986 to March 1987 *(Tracton et al., 1989).* Currently, the breeding growing modes method is used to generate ensembles of 2-week forecasts *(Toth and Kalnay, 1993).* The Chinese Meteorological Centre uses their T42L10 model for operational monthly forecasts *(Zeng et al., 1993),* the European Centre for Medium-range Weather Forecasts produced a set of 30-day integrations from 1985 to 1988 *(Palmer et al., 1990),* and now does seasonal runs. At Me`te`o-France, a global T42 version of the French numerical prediction model was used to predict northern hemisphere winter months from 1983 to 1990 *(Deque and Royer, 1992)* and the Canadian Weather Service *(Ritchie et al., 1994)* has produced forecasts on a monthly scale.

The earliest form of forecasting was synoptic weather forecasting that was initiated by *Multanovsky and Walker* at the beginning of 20th century, lasted on to the 1930's. The analysis of this approach shows that their practical application is controversial. Stable and reliable global or regional schemes have to be developed. Then evolved the statistical and in recent past the dynamical numerical weather prediction *(Muraviev and Vilfand, R.M.).*

2.4.1. Statistical Techniques

There are a wide variety of methods in statistical downscaling, ranging from simple interpolation, regression and analog methods, to more complex techniques such as artificial neural networks *(Tolika et al. 2007; Robertson et al. 2007; Schoof et al. 2009).* The focus is to develop relationship between different variables like pressure, sea surface temperature, etc., as a function of weather by regressing to large amount of historical data.

As far as Indian experience is concerned the main aim had been to forecast the monsoon rainfall as it is very vital for the country. During 1988 to 2002, the IMD issued a forecast for ISMR using a power regression model based *(Gowariker et al., 1991)* on the relationship of the ISMR with 16 predictors, which are based on different facets of the state of the atmosphere and ocean over different parts of the globe. The forecast failure in 2002 prompted IMD to critically examine the 16-parameter model and introduce several new models *(Rajeevan et al., 2003),* which gave correct forecast in 2003. However, the new models failed in 2004, with the predicted ISMR of 100% of the average being much higher than the observed ISMR of 87% of the average. *Iyengar and Raghukanth, 2004* at the Indian Institute of Science (IISc), Bangalore, had predicted a deficit of 5.75% on the basis of a new model developed by them. This model is also based on the observed time series of ISMR. *Kishtwal et al., 2003* predicted a 2% deficit using a new empirical model that they developed based on a genetic algorithm, which also makes use of only the observed rainfall time series. Thus, among the forecasts based on empirical models, the forecast by *Iyengar and Raghukanth* came closest to the observed in sign and magnitude of the anomaly, but none could predict accurately the large deficit of the 2004 monsoon rainfall (*Gadgil et al., 2005).* IMD prepares operational long range forecasts for the Winter Precipitation (Jan to March) over Northwest India and Northeast Monsoon rainfall (October to December) over South Peninsula. For this purpose, separate statistical models have been developed.

2.4.2. Numerical Weather Prediction Models

Though the statistical approach has provided some useful predictive skill, it has not shown significant improvement in the skill during the last several decades due to inherent problems such as the non-stationarity of the climate data series, inter correlation among the predictors, changing predictability, uncertainty in the prediction selection etc. Further, the skill of the statistical models to predict over small regions (such as homogeneous regions, states, districts) and for smaller time scales (months/bi months) is still small due to the higher variability of rainfall over the smaller scales and due to the difficulty in identifying useful and enough predictors for the purpose. In addition, the statistical models generally attempt to predict complex interactions without any specific links to the underlying physical and dynamical processes. This means that they work best when large-scale developments are well and truly under way, but they have difficulty anticipating shifts from, say, warming to cooling or vice versa. As a consequence, they often miss sudden developments (*Willem et al., 2009).*

Further improvements to the prediction weather on a monthly to seasonal scale will be best achieved by using general circulation models (GCMs). A GCM uses numerical weather prediction technique. It also integrates the influences of global SSTs on climate, thus it may have the potential to predict large scale circulation patterns that influence local rainfall *(Higgins et al. 1998; Davis et al. 1997; Von Storch and Navarra, 1995; Stahle and Cleaveland 1992).* A range of studies *(Martin et al. 2000; Sperber and Palmer 1996; Ju and Slingo 1995)* has shown that GCMs are much more successful in reproducing the interannual variations in the large-scale circulation than in the rainfall over India. Unfortunately, GCM forecasts suffer from coarser resolutions making them less exploitable for real-time applications at finer scales.

Thus, two approaches are popular in downscaling the global numerical models' output and improving its usability in regional level. One approach is to use statistical methods of using observed relationships between variables at different scales to estimate finer scale properties to downscale. Lot of techniques like neural networks, canonical correlation analysis, etc., were developed to relate the local weather variables with the GCM outputs and to statistically downscale the weather outputs from GCM. The methodologies are explained and documented by *Willem et al., 2000, 2009; Mxolisi et al., 2006;Fowler et al,. 2007*.

For the same reason mentioned earlier, due to the backlogs in statistical techniques, dynamical downscaling came into wide existence. The major drawback is that the observed relationships may not persist on a changing climate. Plenty of successful attempts on downscaling dynamically were done globally. *Tracton et al., 1989; Ritchie et al., 1994; Deque and Royer, 1992* supported the use of dynamic regional circulation models to downscale the global model outputs.

The numerical prediction (dynamical) models have the potential for providing predictions over smaller spatial and temporal scales as per the user demands. There had been a huge study in this field. *Dickinson et al. 1989; Giorgi and Bates 1989; McGregor 1997; Christensen et al. 2007* have individually verified the use of the regional climate models for the downscaling of the GCM outputs. RCMs, forced by GCMs or by reanalysis data, are able to capture physically consistent regional and local circulations *(Giorgi and Mearns 1991, 1999; Laprise 2008; Leung et al. 2003; Wang et al. 2004)* at the required horizontal and temporal scales, allowing for the development of high-resolution climatologies in any terrain conditions.

In Indian scenario, based on the experiences with statistical models and a range of failure IMD accepted that long-range forecasts with a higher resolution in time and space scales can be generated by dynamical models which can handle far better, the complex regional-scale interactions and manifestations of regional rainfall variability. IMD has already initiated the implementation of a dynamical seasonal prediction system. However, dynamical models do not yet have sufficiently high skill to accurately simulate the salient features of the mean monsoon and its variability. Super-ensemble-type dynamical model predictions are found to improve the skill in prediction of monsoon rainfall.

The Weather Research and Forecast model (WRF), *Skamarock et al. 2008* has been developed as a research and operational numerical weather prediction model, but is increasingly used as an RCM *(Bukovsky and Karoly 2009; Caldwell et al. 2009; Flaounas et al. 2011; Leung and Qian 2009; Liang et al. 2005; Lo et al. 2008; Zhang et al. 2009)*. All these studies showed the ability of WRF to correctly describe climate statistics in different regions, justifying its use as an RCM. Recently, *Caldwell et al. (2009)* used WRF at resolutions of the order of 10 km to dynamically downscale NCEP-NCAR reanalysis in California, *Zhang et al. (2009)* did a similar study for US North Pacific region, and *Heikkila¨ et al. (2010)* looked at the Norway climate. The latter study emphasizes significant improvement from the use of 10 km resolution, even in the representation of mean climate properties, but more importantly in the case of extremes. *Mohanty et al., 2013* demonstrated the usability of WRF models for the prediction of track, intensity, rainfall and structure of 6 tropical cyclones over Bay of Bengal.

WRF is a limited area model which uses the boundary conditions for its domain from the global models, hence the forecast capability is reduced to the forecast lead time of the global models and the artificial boundaries between regions can create forecasting problems. Global WRF is adapted from community development at Cal Tech for planetary atmospheres. It is a functional system for nested non-hydrostatic global simulations *(Skamarock et al., 2008).* It forecasts the state of the atmosphere globally with a single initial file known as first guess, the output of which acts as boundary condition for the nest and can go up to regional level. The feedbacks from nests can also be adapted back to the parent domains thus enabling a two-way feedback system. This way short to long range forecasts can be generated from Global WRF for regional level. NCAR (National

Centre for Atmospheric Research) researchers tested the ability of this cutting-edge regional weather model to stretch out to global scale. They did a 10-day forecast starting with observed conditions on July 12, 2007, at 12:00 Coordinated Universal Time (UTC), or 8:00 a.m. Eastern Daylight Time. The fine-scale details in emerging fronts and storms were visible as water vapour circulates in the atmosphere. Several tropical depressions on either side of the Pacific grow into full-fledged tropical cyclones. The model captured, for example, the passage of Super Typhoon Man-Yi as it rolls over Japan's southern islands and sweeps north, starting around July 13. This is a new field of research with very less papers published in this aspect *(Richardson et al. 2007)*.

2.5. Fine-tuning of Land surface parameters for improved foresight of Weather

2.5.1. Role of land surface in boundary layer processes & atmospheric circulation

Vegetation is one of several parameters that play an important role in land–atmosphere interactions by helping to determine the partitioning of the surface sensible and latent heat flux. *Ookouchi et al, 1984* showed that solenoidal circulations are able to develop between patches of moist and dry soil. Similarly, areas of very dense vegetation next to bare soil surfaces under favorable environmental conditions promote sea-breeze type circulations were proven by *Segal et al. 1986*. Observations indicate that harvesting winter wheat alters the surface sensible heat flux, such that afternoon cumulus clouds develop over harvested fields before they form over adjacent areas with an active green canopy, *Rabin et al. 1990*. *Markowski and Stensrud, 1998* further show that the harvesting of winter wheat over *Schwartz and Karl, 1990* find there are statistically and practically significant relationships between the timing of the onset of vegetation and surface daily maximum temperature. Their study demonstrates at least a 3.58 C reduction in surface daily maximum temperature at an agricultural inland area over any 2-week period subsequent to first leaf compared to a 2-week period prior to first leaf. Stations generally near major bodies of water show a smaller (1.58 C) reduction. *Pielke et al., 1997* confirmed the significant role that land-use change has in generating thunderstorms. Vegetation also has a strong influence on seasonal climate, as shown in a modeling study by *Lu and Shuttleworth, 2002.* Inhomogeneities in land surface interactions create differences in the boundary layer and mesoscale flow *(Pielke and Zeng 1989; Pielke et al. 1991)*. *Chang and Wetzel, 1991* conclude that spatial variations of vegetation and soil moisture affect the evolution of surface baroclinic structures through differential heating. In addition, they found that without the effect of vegetation tapping the root zone soil moisture, the cooling due to surface evaporation alone is too weak to correctly predict the absolute magnitude of the surface temperature or its horizontal variability. Furthermore, soil moisture and vegetation cover variability affect the development of deep convection over land *(Clark and Arritt 1995; Pielke 2001)*. The LAI, a measure of the vegetation biomass, is defined as the sum of the one sided area of green leaves above a specified area of ground surface and it plays a major role in determining the amount of transpiration from the vegetation canopy. Holding all other parameters constant, a larger LAI value produces greater canopy transpiration than a lower LAI value. Hydrological processes (e.g., evaporation and transpiration), energy exchanges (e.g., latent heat and sensible heat fluxes), momentum exchanges (e.g., roughness length), and biophysical parameters (e.g., vegetation albedo, transmissivity, and stomatal conductance) are parameterized to have a strong dependence on the value of LAI. Fractional vegetation cover acts as a horizontal component adjusting the interception of the incoming solar radiation and has an effect on temperature by adjusting the evaporation as a weighing factor between bare soil and canopy transpiration while the leaf area index acts as a vertical component responsible for canopy resistance to transpiration. Both together are important structural properties of land surface areas occupied by plant canopies, and also yield complementary information to describe the 3d structure of the surface land cover. *(Lu and Shuttleworth, 2002)*

2.5.2. Significance of Land Surface parameters in Numerical Models

As a result of the important role that vegetation and terrain height plays in land surface and land–atmosphere interactions, it needs to be represented adequately in numerical weather prediction models. Weather forecasters have a practical sense of this dependence of error growth on initial state; certain types of atmospheric flow are known to be rather stable and hence predictable, others to be unstable and unpredictable. As such, a key to predicting forecast uncertainty lies in the estimation of the effects of local instabilities in regions of phase space through which a forecast trajectory is likely to pass. Thus in NWP's a proper representation of the above mentioned local instabilities will definitely help in improving the model's performance. The local instabilities can be captured from the local surface characteristics like terrain height, land use land cover, fractional cover of vegetation, leaf area index, etc. In mesoscale atmospheric modelling, a variety of surface features such as the elevation, surface roughness, and sensible and latent heat fluxes must be represented in the model *(Pielke, 1984; Lee, et.al., 1991).* These features, expressed in the form of model boundary conditions, must be developed from geographical databases in a way that balances the need for descriptive detail and accuracy with the spatial discretization of a specific model simulation. This is due to both the physics and numerical techniques in a model and to the close coupling of the land surface with boundary layer phenomena under many conditions *(Pielke, 1984). Dirmeyer, 1994* for instance, showed that the inclusion of dormant vegetation during the spring and early summer in a GCM run greatly reduces surface moisture fluxes by eliminating transpiration from leaves, and prevents further depletion of moisture in the root zone of soil, leading to soil-moisture recovery during the subsequent summer. *Xue, 1997* investigated the impact of land surface degradation in the Sahel on seasonal variations of atmospheric and hydrological components over tropical North Africa using a GCM. He found that desertification increases the surface air temperature and reduces precipitation, runoff, and soil moisture over the Sahel region during the summer months. This impact is not limited to the desertified area but also propagates to the south and extends into winter months. Another study, conducted by *Xue et al., 1996* using the Center for Ocean–Land Atmosphere Studies (COLA) GCM, found that the erroneous prescription of crop vegetation phenology in the surface model contributed greatly to the temperature biases of summer simulation in the United States. From previous studies, it is apparent that Differential heating of the planetary boundary layer (PBL) due to heterogeneity in the underlying earth surface gives rise to atmospheric circulations over a wide range of spatial and temporal scales (*Segal and Arritt,* 1992). Increased latent heat flux humidifies the planetary boundary layer (PBL) and increases the moist static energy (MSE) of near surface air and also increase the potential for precipitation *(Eltahir, 1998; Skula and Mintz, 1982; Sud and Fennessy, 1982). Fischer et al., 2011* showed that uncertainties in land surface parameters may lead to large changes in the tails of the distributions in a climate model. Soil moisture specification, LAI, surface roughness, and surface albedo also are important in partitioning the surface energy budget and methods for improving their initialization, such as the Land Data Assimilation System *(Mitchell et al. 2000)*, should be vigorously pursued. With landuse landcover as the base, two important vegetation parameters that are used within numerical weather models are the green vegetation fraction (horizontal component) and the leaf area index (LAI) (vertical component). The role of vegetation parameters in WRF is to determine three components of evapo-transpiration (soil evaporation, wet canopy evaporation, canopy transpiration) and surface energy balance in Noah land surface model. This along with digital elevation model has influence on determining the displacement height and roughness length in the lower surface level modulates the surface heat fluxes and determines the exchange coefficients within the planetary boundary layer *(Chen and Dudhia, 2001)***.** Walker et al., 1995, tried to study the relationship between these aspects of geographic data and the performance of mesoscale atmospheric models and particularly focused on elevation data and how it is prepared for use in such models. They explained that elevation data has a particularly critical role in most mesoscale models, not only because it defines the shape of the lower boundary but the landform also affects the spatial discretization throughout much of the grid volume. This is because such models typically incorporate some form of terrain-following coordinate system where the terrain surface is defined as one limit of a transformed vertical coordinate (e.g., 0) and the top of the model domain is defined as the other limit (e.g., 1). In physical coordinates, the grid points are compressed and stretched as the terrain rises and falls. Thus the landform not only affects the details of the surface interactions, but it also affects the geometry of the grid above the surface. Therefore, the manner in which the terrain is represented can have effects on the numerical representation of the flow throughout much of the grid. Given the complexity of the physical processes just above the land surface and their relatively small length scale, using greater resolution near the ground is usually necessary in mesoscale models that explicitly model the behaviour of the planetary boundary layer.

2.5.3. Impact of updating the representation of land surface conditions on weather simulation

Better representation of the near surface land parameters lead to increase in the quality of weather forecast generated. Among the significant land surface characteristics, leaf area index, soil moisture, topography, fractional vegetative cover, roughness length and albedo play a major role *(Crawford et al., 2001; Wetzel and Chang, 1998)*. *Ravindranath et al., 2010* utilized the AWiFS dataset, a high resolution updated dataset when compared to the existing USGS dataset. The study proved the improvement not only in the micro-meteorological features but also influences positively the large scale circulation patterns upto 850mb. *Sertel et al., 2009; Cheng et al., 2013* also accepted the same fact in their studies. Using near-real-time satellite-derived values of vegetation fraction and LAI improves the 2-m temperature simulations of the fifth-generation Pennsylvania State University–National Center for Atmospheric Research Mesoscale Model (MM5) when using the Parameterization for Land–Atmosphere–Cloud Exchange *(Wetzel and Boone, 1995)* for the land surface *(Crawford et al. 2001).*To explore the importance of the initial state vegetation characteristics on operational numerical weather forecasts, the response of the Eta Model to initializing fractional vegetation coverage (Leaf Area Index and Vegetation Fraction) directly from the National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (AVHRR) data was investigated by *Kurkowski et al., 2002*. Results show that use of the near-real-time vegetation fraction data improved the forecasts of both the 2-m temperature and dewpoint temperature for much of the growing season, highlighting the need for this type of information to be included in operational forecast models. *Cheng at al., 2005* evaluated the Surface Sensible Weather Forecasts over western united states.The results suggest that improvements in LSM initialization may be as or more important than improvements in LSM physics. *Anil Kumar et al., 2011* tested the impacts of integrating MODIS vegetative parameters like Leaf Area Index, Landuse Landcover and green vegetation fraction with the WRF model for regional weather prediction. Overall results suggest that WRF with MODIS based LAI and GVF reduced latent heat flux roughly 100-150 W m-2 over east side of domain in comparison with USGS landuse + Table LAI experiments done with WRF. The bias in the surface temperature prediction also decreased reasonably. Similar results were also obtained in the studies conducted by *Oleson and Bonan, 2000; Lixin Lu and Shuttleworth W.J., 2002; Toshihisa Matsui and Venkataraman Lakshmi, 2005; Jianjun Ge, 2008; Christopher M. Godfrey, David J. Stensrud., 2010; Kumar et al., 2013*. They collectively demonstrated the positive feedback, the updating of land surface parameters have on meteorological variables. *Zhang et al., 2013* in their paper illustrated the increase in the error of surface temperature and wind speed prediction due to mismatch in the model's representation of terrain and the actual terrain. *Walker and Leone, 1994* concluded that the simulated low-level wind fields along with the distribution of precipitation show significant dependence on the terrain representation used in the simulations. When the appropriate terrain was used for California, the simulated barrier jet was intensified by over 2.5 ms-1.It also enhanced the low-level vertical motion by 10-30%. This intensified barrier jet and low-level vertical motion enhanced precipitation in northern Coastal Range and Sierra Nevadas and may be very important in achieving accurate precipitation forecasts that can be used to drive hydrologic models of crucial watersheds. Walker et al., 1995 mentioned in his study over California that at smaller spatial scales, nocturnal drainage winds in mountain valleys in Colorado are examined for effects on the general characteristics as well as the details of the flows. At the larger end of the mesoscale, extended simulations of California weather are examined for effects on orographic lifting, low-level convergence and divergence and ultimately rain and snow distribution. The conclusions showed that, the terrain representation can have significant effects on the simulated flow that could be important in some applications.

2.6. Composite Approach of Regional Crop yield forecasting

From the collection of references ample research in crop yield forecasting is obvious. Yet there is no one single methodology that had proved its efficiency in the field. Combining different approaches will definitely lead to development of an improved methodology that can stand superior to the individual approaches. This section is a compilation of such integrated approaches so far and way ahead.

2.6.1. Remote Sensing Technique for Crop Acreage & Yield Estimation

With the advent of Remote Sensing (RS) technology during 1970s, its great potential in the field of agriculture have opened new vistas of improving the agricultural system monitoring all over the world. Space borne satellite data have been widely used in the field of agriculture for estimation of area under different major crops. *Sahai and Navalgund, 1988* described the IRS utilization programme in agriculture. Remote Sensing proved fruitful for crop acreage estimation especially for large homogenous areas.

Verma et al., 2011 used remote sensing techniques in crop acreage assessment. Crop acreages were estimated using the particular season's Indian Remote Sensing Satellite data. Stratified Random Sampling approach and supervised classification of Satellite digital data have been adopted for district-level acreage estimation. In this procedure, using ground based observations collected synchronous to satellite passes, the various crops along with other vegetation classes were identified on the satellite data and spectral signatures were generated for supervised classification. The sample segments were classified using these spectral signatures and crop acreages in the district are estimated using standard statistical aggregation procedures.

Potgieter and Andriesto, 2009 used MODIS EVI to determine broad acre crop area estimates through the use of multi-temporal satellite imagery for major Australian winter crops. Multi-temporal approaches comprising principal component analysis (PCA), harmonic analysis of time series (HANTS), multi-date MODIS EVI during the crop growth period (MEVI), and two curve fitting procedures (CF1, CF2) were derived and applied. These approaches were validated against the traditional single-date approach. Early-season crop area estimates were derived through the development and application of a metric, i.e. accumulation of consecutive 16-day EVI values greater than or equal to 500, at different periods before flowering.

Oza et al., 2006 in their paper described the methodology adopted and results obtained during forecasting of national level wheat production in India using multi-date medium resolution Advanced Wide Field Sensor (AWiFS) data. Multidate, geometrically registered and radiometrically normalized Resourcesat-1 AWiFS data were classified using hierarchical decision rules, which exploited differential crop spectral profiles of various crops in winter season. Wheat acreage estimates were arrived by aggregation of stratified samples. Wheat yields were predicted for meteorological sub-divisions by correlation weighted weather regression models developed using fortnightly temperatures. Multiple preharvest wheat acreage and production forecasts were made with additional information on spatio-temporal crop growth performance in comparison to previous / normal season. Jongschaap et al., 2005 integrated Remote Sensing derived parameters in local crop simulation model (Rotask) to forecast yield of wheat at regional level in southeast France.

2.6.2. Sowing Date Assessment using Remote Sensing

Muratova & Terekhov, 2004 tried an approach to estimate the crop calendar dates of spring crops by using MODIS reflectance images. The spectral characteristics positive increase of infrared band was used to arrive at the sowing dates. *Vyas et al., 2013* used daily operational Normalized Difference Vegetation Index (NDVI) product from INSAT 3A CCD available through Meteorological and Oceanographic Satellite Data Archival Centre (MOSDAC) to estimate sowing date of wheat crop in selected six states. The characteristic temporal profiles of 7 day NDVI composite was used to determine sowing date. NDVI profile showed decreasing trend during maturity of kharif crop, minimum value after harvest and increasing trend after emergence of wheat crop. A mathematical model was made to capture the persistent positive slope of NDVI profile after an inflection point. The change in behaviour of NDVI profile was detected on the basis of change in NDVI threshold of 0.3 and sowing date was estimated for wheat crop in six states.

2.6.3. Integrating Approaches for Regional Forecasting of Crop Production

Variability by itself is not necessarily welfare decreasing if it is anticipated and acted upon. Surprise, however, has adverse consequences since the optimal ex post and ex ante choices rarely coincide *(Hallstrom, 2004). Hansen, J. W., 2005* briefed the need for integrating crop-climate systems. He explained the integration can help overcome existing problems like mismatch between farmers' needs and available forecasts, risks and time associated with adaptation and adoption to the uncertainties, challenge in obtaining institutional, financial and political support, etc. He also compiled the integrated approaches so far developed. He strongly supported the integration of crop-climate models for betterment of the forecasts. *Richard A. Betts, 2005* in his paper discussed the need for a more integrated approach to modelling changes in climate and crops, and some of the challenges posed by this. He discussed three streams of this integration. One was to integrate climate model outputs with crop models to improve the applicability of the forecasts in real-time. The second and third stream involved crop model implementation into the climate models to improve the representation of the land processes to simulate better state of atmosphere. *Bryan C. Weare, 1990* had foreseen the scope of climate models into the crop model and its usefulness in issuing the forecasts in spatial and temporal scales. At that instance he also discussed the problem of using Global Circulation Model directly into the crop model due to its coarser resolution, now the problem stands a little solved due to the availability of regional climate models. He also addressed that even if inaccuracies exist, how best to use the crop predictions. One question, for instance, is whether there are any management decisions likely to be profitable that can be made using a 10-day crop forecast with an average skill of 50%. The ultimate goal must be to maximize the utility of predictions given realistic assessments of their uncertainties. *Das et al., 2010* briefed the Accuracy, usefulness and main limitations of weather forecasts at different time scales in context to agriculture. They compiled the types of weather forecasts based on lead times into five types as nowcasting, very- short range weather forecasting, short-range forecasting, medium- range weather forecasting and long-range weather forecasting. The weather inputs for agriculture as discussed in the above sections are very critical to the crop model. If weather forecasts are available with known accuracy at various lead times then it is not that tough to forecast the crop model at different time scales.

Methods proposed for linking crop models with dynamic seasonal climate forecasts include classification and selection of historic analogs, stochastic disaggregation, direct statistical prediction, probability-weighted historic analogs, and use of corrected daily climate model output. Lot of research involved statistical approaches to forecast the weather based on historical weather data like stochastic weather generators were used to forecast the crop yield within season as in the study by *Bannayan et al., 2004; Lawless and Semenov, 2005*. These proved to be site-specific, data intensive, spatial invariable and the link to process based scientific background to be missing. Another limitation of using generated data lies in the fact that although the means of crop yields may be produced, the variances and frequencies of extreme events are not always captured by the generated data *(Mearns et al., 1996, 1997).*

The studies by *Hanley et al., 2002*; *Baigorria et al., 2007; Challinor et al., 2005; Ines and Hansen, 2006;* utilized daily GCM/RCM outputs for direct use by crop models. The results from these studies indicate that the regional climate model exhibits some skill in the prediction of crop yields. Valentin et al., 2000 has used weather data from mesoscale meteorological model (MESAN) as input to WOFOST (WOrld FOod STudies) crop model to improve yield prediction of spring barley, spring rape, oats and winter wheat in Sweden. For a semi-arid location in Kenya, *Hansen, J.W.,and Matayo Indeje, 2004* demonstrated and evaluated methods to predict field-scale maize yields, simulated by CERES-maize with observed daily weather inputs, in response to downscaled seasonal rainfall hindcasts available prior to planting, derived from an atmospheric general circulation model, ECHAM. The methods considered were statistical prediction by non-linear regression, probability-weighted historic analogs and stochastic disaggregation to predict field-scale maize yields simulated by CERES-maize with observed daily weather inputs. Downscaled ECHAM output predicted 36% of the variance of total precipitation and 54% of the variance of rainfall frequency in October–December at the site. Non-linear regression showed the lowest and stochastic disaggregation showed the highest overall error. All of the yield forecasting methods showed similar random error, predicting from 28 to 33% of the variance of yields simulated with observed weather. Incorporating the predictability of rainfall frequency into the stochastic disaggregation procedure did not improve yield predictions. Based on this study, stochastic disaggregation, direct statistical prediction and probability-weighted historic analogs all show potential for translating seasonal climate forecasts into predictions of crop response. An ENSO based seasonal climate analysis tool (RAINMAN) was used by *Zinyengere et al., 2011* to produce probabilistic monthly climate forecasts for Masvingo corresponding to the phases of the Southern Oscillation Index (SOI). The climate forecasts were used to run a crop model (AquaCrop) for a variety of scenarios relevant to maize production (monthly rainfall, cultivar selection, planting date, and fertility level). The results of the simulations were similar to those observed by Phillips et al., 1997 and formed the basis for the development of an operational decision support tool. Simulated maize yields varied from 1.2 t/ha to 5.8 t/ha. *Baigorria et al., 2006* in their study, used 20 ensemble members of an 18-year period provided by the Florida State University/ Center for Ocean-Atmospheric Prediction Studies (FSU/COAPS) regional spectral model coupled to the National Center for Atmospheric Research Community Land Model (CLM2). The daily seasonal-climate hindcast was bias-corrected and used as input to the CERES-Maize model, thus producing 20 crop yield ensemble members. Using observed weather data for the same period, a time series of simulated crop yields was produced. Finally, principal component (PC) regression analysis was used to predict this time series using the crop yield ensemble members as predictors. Bias correcting all meteorological variables used by the crop model increased predictability skills compared with use of raw hindcasts, individual bias-correction of rainfall, and climatological values.

Abundant studies are thus made on this specific aspect yet the uniqueness of the study is that it combines regional climate model, crop model and geomatics under a single platform increasing the applicability of the crop yield forecasts on a regional level with high temporal resolution. Focusing on a more refined field of the research in the present day, the project focuses to study the two way feedback, i.e. the feedback land surface vegetative parameters gives to atmospheric modeling and also the feedback the atmospheric weather forecasts gives to crop model to simulate the crop yield.

Chapter 3

STUDY AREA & AGRONOMIC REVELANCE

The approach is demonstrated over the wheat cultivating plains of Punjab and Haryana. The significance of the study area with respect to the wheat crop is discussed in this section.

3.1.Socio-economic & agronomic aspects of wheat crop

3.1.1. Significance of Wheat economy in India

Wheat plays an important part in the Indian food economy. India is one of the principal wheat producing and consuming countries in the world. Its importance in Indian agriculture is second to only rice. Wheat is cultivated in an area of around 25 million hectares which represents a fifth of the total area under food grains in India. Around 80 per cent of the area under wheat is irrigated. Nearly 70 million tonnes of wheat is produced in India every year. From a global point of view, the wheat area in India accounts to 11% of the total area under wheat cultivation across the globe and about 12% of the global wheat production. Nationally about 18 per cent of the net cropped area is planted to wheat. Uttar Pradesh (U.P.) contributes the largest share with 36 per cent of production, followed by Punjab with 19 per cent and Haryana with 11 per cent. These three northern states together contribute two-thirds of the production of wheat. These are followed by Madhya Pradesh (M.P.) 11 per cent, Rajasthan 10 per cent, Bihar 6 per cent and Gujarat 3 per cent. All the rest contribute only 4 per cent.

Wheat has made the largest contribution to the growth of food grain production in India. This is shown by the growth rates: wheat production has grown at a much faster pace compared to other food grains. During 1950/51-2000/01, when total food grain production grew at an annual rate of 2.68 per cent, wheat production grew at 5.36 per cent. Even in the last decade, wheat production is showing the fastest growth, though a slowdown is evident. Another feature of wheat production is that the wheat yields vary substantially across the states. Punjab and Haryana show the highest yields of 3853 and 3660 kg/ha, respectively. These are followed, after a significant gap, by Rajasthan, U.P. and Gujarat with 2500, 2498 and 2373 kg/ha respectively – which are close to the national average of 2583 kg/ha. Bihar and M.P. follow with much lower yields of 1999 and 1625 kg/ha, respectively. These yields can be compared with 2907 kg/ha in USA, 1907 kg/ha in Australia, 1029 kg/ha in Russia, 3667 kg/ha in China and 7603 kg/ha in France *(FAO*

1998). Though Uttar Pradesh has the highest production In India, it lags behind Punjab and Haryana in terms of yield. Better irrigation facilities in these states are responsible for higher yield. In Haryana, 98 per cent of the area under wheat is irrigated and in Punjab the ratio is 96 per cent. However, in Uttar Pradesh, only 88 per cent of the area under wheat is irrigated.

3.1.2. Season

Wheat is a Rabi crop, grown in the winter season. Sowing of wheat in general takes place in October to December and harvesting is during February to May. The Indo-Gangetic plains in India are the most conducive area in India for growing wheat. The cool winters and the hot summers are the perfect conditions for a good wheat crop.

3.1.3. Areas under cultivation

India is broadly divided into 5 wheat zones based on agro-climatic conditions:

- The **North-Western Plains Zone**: This is the most important zone consisting of the plains of Punjab, Haryana, Jammu, Rajasthan (except the south-eastern portion) and western Uttar Pradesh. The wheat here is planted in late October – November and the harvesting usually begins by middle of April.

- The **North Eastern Plains Zone**: This zone consists of eastern Uttar Pradesh, Bihar, West Bengal, Assam, Orissa, Manipur, Tripura, Meghalaya, Nagaland, Mizoram, Arunachal Pradesh and Sikkim. As there is late harvesting of paddy in these areas, wheat is mainly sown in late November or early December. Harvesting is done by March – April.

- The **Central Zone**: This zone consists of Madhya Pradesh, Gujarat, south eastern Rajasthan (Kota and Udaipur area) and the Bundelkhand area of Uttar Pradesh. Almost 75% of wheat cultivated in this area is rainfed. The best quality durum wheats are produced in this zone.

- The **Peninsular Zone**: The peninsular zone consists of the southern states of Maharashtra, Andhra Pradesh, Karnataka, and Tamil Nadu. Sowing in this zone is mostly complete by early November and the harvesting starts in second half of February. The duration of the wheat crop is the earliest in this region.

- The **Northern Hill Zone**: This zone consists mainly of the hilly areas of Kashmir, Himachal Pradesh and Uttar Pradesh, West Bengal, Assam and Sikkim. The sowing in this zone is done in October and the harvesting is done in May-June. The crop remains almost dormant in the cold months from November to March and as the temperature rises in April the crop starts growing.

3.1.4. Soil, Seed Quality and Field Preparation

Well-drained loams and clayey loams are considered to be ideal for wheat. Good crops of wheat have also been raised on sandy loams and the black soils. The seed used for sowing should have good germination capacity and should be healthy and free from seed borne diseases and seeds of weeds. Experts suggest sowing of certified seeds obtained from a reliable seed agency. For good and uniform germination, the wheat crop requires a well pulverised but compact seedbed. It is also essential to do timely cultivation and conserve moisture.

3.1.5. Sowing Practices

Usually wheat seeds are sown by drilling or broadcasting. Sowing with drills either tractor or bullock driven, ensures that the seed is deposited at a uniform depth. In a number of places, seed is also sown by hand, behind the plough drawn by the bullock. For timely sown and irrigated wheat, a row spacing of 15 to 22.5 cm is followed. 22.5 cm is considered to be the maximum spacing. For late but irrigated wheat, row spacing of 15-18 cm is considered to be the maximum.

For dwarf varieties, planting depth should be between 5-6 cm. In case of conventional tall varieties, the sowing depth may be 8 or 9 cm. Usually, deeper sowing is done in dry, rough and light soils, whereas shallow sowing is done in moist soils. If the sowings are much delayed, transplanting of wheat seedlings can be done. Under rainfed conditions, the furrows are left open after sowing, whereas in case of irrigated wheat, a wooden plank covers the furrows. The first experience of Indian scientists growing dwarf wheat was unhappy because of poor stands. A critical examination revealed that the coleoptiles of most of the sown seeds could not reach surface and stayed buried deep into the soil. It became clear that the sowing depth of 15 cm as practised for tall wheat varieties was not suitable. Thorough laboratory tests showed that dwarf wheat had shorter coleoptiles than tall one; as a result a large number of seeds lay buried into the soil. Detailed studies on the depth of sowing with the dwarf varieties showed that shallow sowing (5-7 cm deep) was optimal. This was one of the most important findings that contributed to the successful establishment of the crop.

The work on sowing depth triggered another curiosity of Indian wheat agronomists to know the optimum time of planting under Indian conditions. Based on a series of well-planned experiments, second or third week of November in the plains of north India was found to be the most suitable time. Further, it was also found that most of the dwarf varieties yielded maximum when sown around 12 November. This was in sharp contrast of the practice of sowing tall wheat in later half of October.

3.1.6. Growth Stages of Wheat

The wheat plant has to pass through the four stages to complete its life cycle. Simplified explanations of the stages are:

- **Pre-establishment stage**

  a. Pre-emergence stage: Sprouting of seeds by giving rise to seminal roots and coleoptiles.

  b. Emergence stage: Appearance of coleoptiles from germinating seeds above the soil surface.

- **Vegetative stage**

  a. Seedling stage: The young plants establish larger root systems at this stage. The stage may be further differentiated as one leaf, two leaf, three leaf and four leaf stages.

  b. Crown root stage: This coincides with three or four leaf stages in which the appearance of crown roots takes place.

  c. Tillering stage: Plant, at this stage, develops crown and starts branching.

  d. Jointing stage: This is the stage at which the plants begin elongating when the nodes start developing above the crown node.

- **Reproductive stage**

  a. Booting stage: This is the stage in which the upper- most leaf swells out into flag holding the spike into it.

  b. Heading stage: In this stage the spike starts emerging out from the leaf sheath.

  c. Flowering stage: Anthesis of florets and fertilization of ovaries occurs at this stage.

- **Post-anthesis stage**

  a. Filling: The ovaries, after fertilization is complete, starts elongation and transform into seeds or ovules passing through milk, soft, dough and hard dough stages.

b. Maturity: Colour of the glumes changes and kernels become fairly hard at this stage. Moisture percentage is gradually reduced and the plant can be harvested at this stage. This is the stage of economic importance.

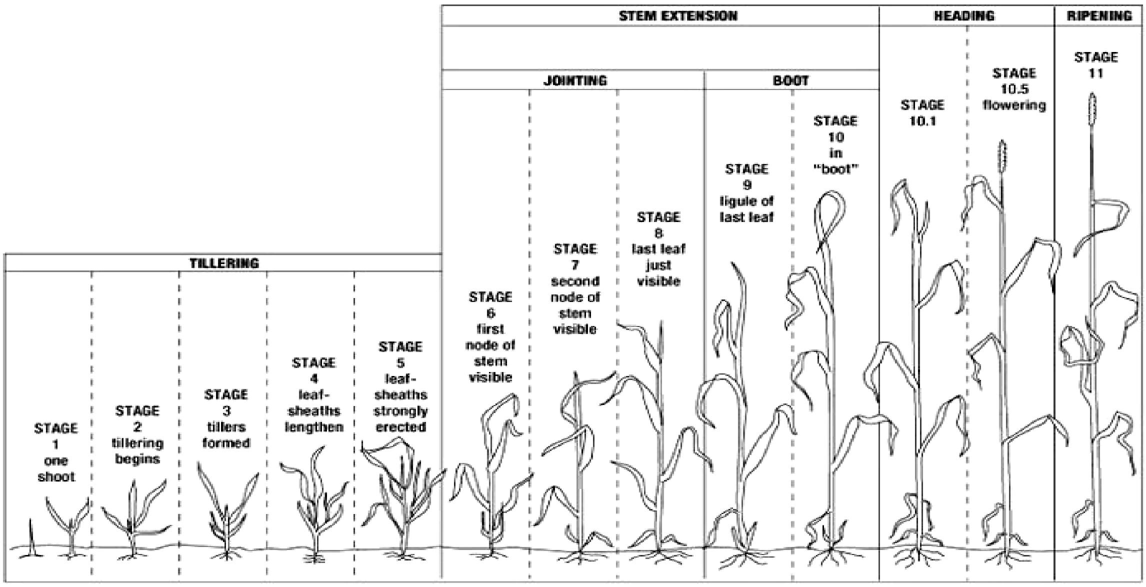


Fig 3.1-The important growth phases in wheat crop

3.1.7. Water Management

Four-Six irrigations are needed for wheat sown under irrigated conditions. The first irrigation to the standing crop should be given 20-25 days after sowing that is at the crown root initiation stage. In cooler regions like hilly tracts and in late sown wheat, it is advantageous to apply first irrigation approximately 25 to 30 days after sowing. Delay in applying this irrigation results in upsetting synchronous tillering, subnormal heads, poor root development and finally poor grain yield. Second irrigation is given at tillering stage, within 40-45 days of sowing. At late jointing stage, within 70-75 days of sowing, the field is irrigated for the third time. At flowering stage, within 90-95 days of sowing the fourth irrigation becomes due. Irrigation at this stage is also important because during this period plants suffer most from soil moisture deficiency. The grain number and size are reduced considerably. At dough stage, within 110-115 days after sowing it has been noticed that if any of these irrigations are delayed or missed, the yield is reduced to the tune of 5-10 quintals/ha.

Irrigation in case the water supply is limited should be given in the following way:

- If the water is available for only one irrigation, it should be given at the crown root initiation stage to the tillering stage.
- If the water is available for two irrigations, the first irrigation should be applied between the crown root initiation and the late tillering stage and second irrigation 7 to 8 weeks after the first irrigation (flowering stage).
- If the water is available for three irrigations, the first should be given at the crown root initiation stage and the next two at intervals of six to seven weeks at the flowering and the milk stages respectively.

It was considered necessary to optimize the irrigation schedule to obtain commensurate yield gains. The investigations revealed that first irrigation was most essential for high productivity, which must be applied 21 days after sowing. About 17 days after sowing crown node starts swelling and crown root develops from this node approximately 21 days after sowing. Tillers develop from the crown root and, therefore, this phase was directly relevant to the number of tillers and final heads and is supposed to be the most critical period of irrigation. Depending on the availability of water with the farmer for irrigation a schedule for the crop growth and development period was worked out. Thus, an optimum scheduling of irrigation taking into account the critical phenological phases was made available to the farmers. Four irrigations, first at crown-root initiation, followed by at flowering, late tillering and milk stages, were found to be optimum, particularly under high fertility conditions.

3.1.8. Harvesting

The wheat crop is harvested when the grains harden and the straw becomes dry and brittle. The harvesting time varies from zone to zone and also depends whether the wheat is under irrigated or rainfed conditions. The rainfed crop reaches harvesting stage much earlier than the former. However, the yields under the rainfed crops are much lower compared to the other because of the extended growth stages.

3.2.The Regions for the Study

3.2.1. Punjab

3.2.1.1. Geographic Extent

Punjab is located in north-western India, and has an area of 50,362 km^2. It extends from the latitudes 29.30° North to 32.32° North and longitudes 73.55° East to 76.50° East. It is bounded on the west by Pakistan, on the north by Jammu and Kashmir, on the northeast by Himachal Pradesh and on the south by Haryana and Rajasthan. It is divided into four administrative divisions and twenty-two districts.

3.2.1.2. Relief

Lying between the Yamuna River on the east and the Indus on the west, fringed by a dissected foot-hill zone and the Shivalik Hills in the northeast and north, Punjab is an extensive alluvial plain. Its average elevation is 300 meters above sea level, with a range from 180 meters in the southwest to more than 500 meters around the northeast border. The southwest of the state is semiarid, initially desertic and undulating, but has gradually turned to arable land by extension of irrigation and cultivation. The Shivalik Hills extend along the north-eastern part of the state at the foot of the Himalayas.

3.2.1.3. Soil

The soil characteristics are influenced to a limited extent by the topography, vegetation and parent rock. The variation in soil profile characteristics are much more pronounced because of the regional climatic differences. Punjab is divided into three distinct regions on the basis of soil types: south-western, central, and eastern.

3.2.1.4. Water Sources

Most of the Punjab lies in a fertile plain, alluvial plain with many rivers and an extensive irrigation canal system. The region is thus a great mass of alluvium brought down by the Indus and the five rivers (Jhelum, Chenab, Ravi, Beas and Sutlej) uniting in the southwest at Panjnad. In between the Yamuna and the Sutlej in the east, the Ghaggar River and its tributaries contributed to the same process of alluvium in what is now called the Malwa Tract. The state is also extensively irrigated. Nearly 4.06 m ha are irrigated by canal and tube-well irrigation systems. The former contributing 27.4 % and the later contributing 70% of the total irrigated area.

3.2.1.5. Climate

Punjab's climate is characterized by extreme hot and extreme cold conditions. Nowadays annual temperatures Punjab range from 1 to 46°C (min/max), but can reach 49°C in summer and 0°C in winter. The northeast area lying near the foothills of the Himalayas receives heavy rainfall, whereas the area lying further south and west receives less rainfall and experiences higher temperatures. Average annual rainfall ranges between 960 mm in the sub mountain region and 460 mm in the plains.

Punjab has three seasons:

- Summer (April to June), when temperature typically rise as high as 43°C.
- Monsoon season (July to September), when a majority of rainfall occurs.
- Winter (December to February), when temperatures typically fall as low as 4°C.

There is a transitional period between winter and summer in March and early April, as well as a transitional season between monsoon season and winter in October and November.

3.2.1.6. Agriculture

The Punjab state has 4.23 m ha under cultivation. Agriculture is a way of life. About 75% of its population depends directly on agriculture. Since the advent of green revolution; the state has made rapid strides in agricultural production. The cropping intensity has increased from 126% to 186% during the period 1965-66 to 2004-05. The area under wheat has increased by 216% and production by 756%, whereas the area under rice has increased by 895% and production by 3307%. The state has played a prominent role by achieving self sufficiency in food grains by contributing 60% wheat and 40% rice to the central pool. The productivity of wheat has increased from 1236 kg/ha to 4209 kg/ha. Though wheat and rice are the major crops it also has intensified agriculture with maize, bajra, cotton, groundnut, sugarcane and potatoes.

3.2.1.7. Agro-Climatic Zones

The State of Punjab has been classified into five agro-climatic zones on the basis of homogeneity, rainfall pattern, distribution, soil texture, cropping patterns etc. These zones are **Sub-Mountain undulating region** which includes districts Gurdaspur and Hoshiarpur and receiving the maximum annual rainfall, **Undulating plain region** with Ropar and Nawanshahr districts coming under this zone, the **Central plain region** including maximum of the districts like Amritsar, Taran Tarn, Kapurthala, Jalandhar, Ludhiana, Fatehgarh Sahib, Sangrur and Patiala, the **Western plain region** covering Ferozepur and , Faridkot and finally the **Western**

region receiving the least rainfall consisting of Moga, Bhatinda, Mansa, Muktsar, Sangrur and Barnala.

3.2.2. Haryana

3.2.2.1. Geographic Extent

Haryana is a landlocked state in northern India. It is located between 27°39' to 30°35' N latitude and between 74°28' and 77°36' E longitude covering an area of 44,212 km^2. It is bounded by Punjab and Himachal Pradesh to the north and by Rajasthan to the west and south. The river Yamuna defines its eastern border with Uttrakhand and Uttar Pradesh. It is divided into four administrative divisions and twenty-one districts.

3.2.2.2. Relief

Most of Haryana is in the plains with the Aravali mountain range starting its westward. The altitude of Haryana varies between 200 metres to 1200 metres above the sea level. The Yamuna is the only major river that passes through this small state. The major geographical divides are theYamuna-Ghaggar plain forming the largest part of the state, the Shivalik Hills to the northeast, Semi-desert sandy plain to the southwest and the Aravalli Range in the south.

3.2.2.3. Soil

The soil characteristics are influenced to a limited extent by the topography, vegetation and parent rock. The variation in soil profile characteristics are much more pronounced because of the regional climatic differences. Broadly the soils of Haryana have been classified into five major groups as reddish chestnust soils, tropical arid brown soils, arid brown soils, seirozem soils and desert/problem soils.

3.2.2.4. Water Sources

Haryana has no perennial rivers. The important rivers are Yamuna, the Saraswati and the Ghaggar. Several small streams flow through the state they are the Markanda, the Sahibi and Indori. Yamuna is the most important river in the state. It has its source in the hills at Kalesar and is the source of irrigation for large tracts in the districts of Ambala, Kurukshetra, Karnal, Hissar and Rohtak through the western Yamuna canals. The river Saraswati begins in the large depression at Kalawar in the north of the Mustafabad Pargana of Jagadhri. The Ghaggar rises in the outer Himalayan ranges between the Yamuna and the Sutlej. Nearly 2.9 m ha are irrigated by canal and tube-well irrigation systems. The former contributing 42.8% and the later contributing 57.2% of the total irrigated area.

3.2.2.5. Climate

The Climate is almost very similar to that of Punjab with 80% of the rainfall occurring in the monsoon season (July–September). Though Haryana lies in the sub-tropical belt but in the state as a whole there are three types of climate: (i) Arid (ii) Semi-arid and (iii) Sub-humid. The normal annual rainfall varies from 300 mm in the south-western parts of Bhiwani and Sirsa districts to about 1560 mm in the north-eastern hilly tract of Ambala district. Wind velocity is maximum in months of May and June (8-11 km/hr). The potential evaporation is 200 mm per annum. Minimum temperature becomes close to freezing in December/ January and the maximum daily temperature is above 40°C in May/June. The mean annual temperature ranges from 23°C to 26°C.

3.2.2.6. Agriculture

The cultivable area is3.7 m ha, this is 84% of the geographical area of the state out of which 3.64 m ha i.e 98% is under cultivation. The gross cropped area of the state is 6.51m ha and net cropped area is 3.64 m ha with a cropping intensity of 184.91%. About 70% of residents are engaged in agriculture. Wheat and rice are the major crops. Haryana is self-sufficient in food production and the second largest contributor to India's central pool of food grains. The main crops of Haryana are wheat, rice, sugarcane, cotton, oilseeds, pulses, barley, maize, millet etc. There are two main types of crops in Haryana: Rabi and Kharif.

3.2.2.7. Agro-Climatic Zones

The State of Haryana has been classified into two major agro-climatic zones on the basis of homogeneity, rainfall pattern, distribution, soil texture, cropping patterns etc. The **north western part** including districts of Ambala, Kurukshetra, Karnal and parts of districts of Jind, Sonepat, Rohtak, Gurgaon and Faridabad are suitable for Rice, Wheat, Vegetable and temperate fruits and the **south western part** comprising of Sirsa, Hisar, Bihwani and some parts of Jind, Rhatak and Gurgaon districts are suitable for high quality agricultural produce, tropical fruits, exotic vegetables and herbal and medicinal plants.

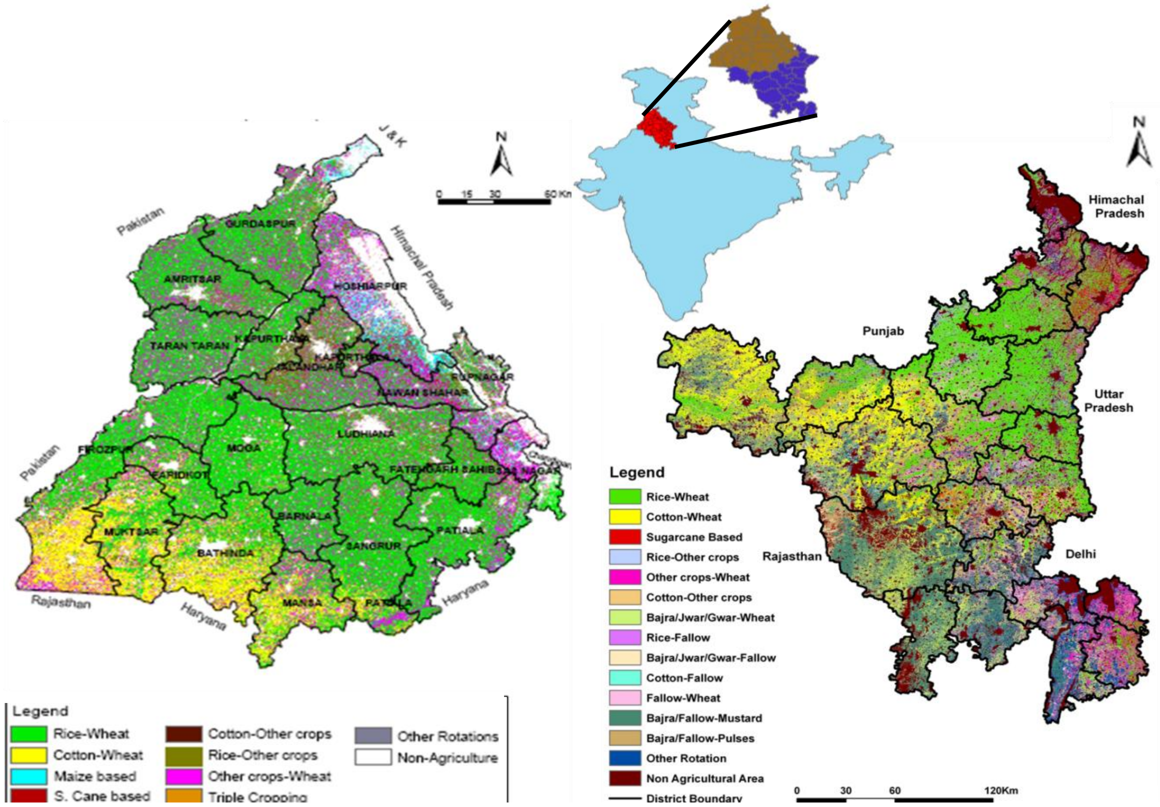


Fig 3.2- The cropping pattern of Punjab (Left) and Haryana (Right). Inner picture depicts the location of Punjab and Haryana with respect to the India map. Source: agricoop.nic.in

3.3.Justification

Wheat is one of the principal crops in India with a gross area of 29.2 m ha and accounting to production of 85.9 m tonnes. As mentioned in section 3.1 it is second only to rice. It contributes a lot to the stabilization of Indian economy having an excellent scope for export since the productions at most of the developed countries are low. Thus forecasting the crop prior to its actual harvest would lead to ample number of benefits and enhance the quality of the decisions. Also the wheat crop is a Rabi crop, which gives more possibility of using optical earth observation images that are freely available for the development of the integrated methodology which is the main objective of the study. The growth stages of wheat are highly vulnerable to weather variables which are a proved fact from various studies (refer to section 2.2). Ceres-

Wheat has been successfully tested in the indo-gangetic plains many a times and the genetic co-efficients of the crop for different growth stages are established earlier.

Punjab and Haryana collectively contribute 30% of the total production and top in the productivity. Both covering nearly 30% (25.4 m ha approx.) of the total area under wheat. Punjab alone gives over 2 million tonnes and more of wheat per annum. Both jointly contributes a total area of which maximum area is irrigated; managed technically; optimal fertilizer inputs; use of almost uniform high yielding dwarf varieties; most favourable unvarying sowing dates; large area coverage (homogeneous parcels).These reasons make it a favourable hub for experimenting crop run with various cases in view of the fact that the crop is in optimal to semi-optimal conditions. Moreover, both the states has achieved self-sufficiency in wheat production thus every scope for export is possible. The study would thus be vital for the area.

The study period is 2008-09 which is a normal year in terms of agricultural output, weather conditions and economics. Thus it is considered appropriate for the study.

Chapter 4

MATERIALS & METHODS

The details about the methods and the materials employed in addressing objectives of the present study are discussed in detail within this section. Since the study is a combination of three approaches, here the materials and methodology are discussed in parts of each approach and finally linking up of various resources into a single platform to achieve the main core objective.

4.1.Input Data

4.1.1. Gridded forcing and terrestrial data

Forecasted weather conditions are generated for a spatial extent and at various temporal degrees by using the regional circulation model WRF-ARW. The implementation of the model requires the following datasets.

4.1.1.1. Forcing Data and Initial Conditions

Real-time regional NWP often uses global forecast for boundary conditions and initial weather conditions. Here the global forecast system (GFS) models output is used for this purpose. It is a gridded data at a resolution of 0.5° and frequency of 3 hourly outputs. The data is downloaded at 12:00 UTC time zone as it is appropriate for India. Nearly 200 and more weather parameters are available from this data like to state a few temperature, relative humidity, wind components, etc at 47 vertical levels. It is maintained by NOAA (National Oceanic and Atmospheric Administration), USA and can be downloaded from http://www.nco.ncep.noaa.gov/pmb/products/gfs/. The archives of the data are available from the year 2005 and available in GRIB 2 (GRIdded Binary) format. The model is run in two parts: the first part has a higher resolution and goes out to 192 hours (8 days) in the future; the second part runs from 192 to 384 hours (16 days) at a lower resolution. The resolution of the model varies in each part of the model: horizontally, it divides the surface of the earth into 35 or 70 kilometre grid squares; vertically, it divides the atmosphere into 64 layers and temporally, it produces a forecast for every 3rd hour for the first 192 hours, after that they are produced for every 12th hour. It is widely accepted that beyond 7 days the forecast is very general and not very accurate.

4.1.1.2. Lower Boundary Conditions

SST data is downloaded from ftp://polar.ncep.noaa.gov/pub/history/sst which is available from 2001. It is at a resolution of 0.5° with a daily frequency in GRIB1 format.

4.1.1.3. Terrestrial Datasets

The terrestrial datasets are downloaded at various resolutions 30", 2', 5', and 10'. http://www.mmm.ucar.edu/wrf/src/wps_files/geog.tar.gz. The terrestrial datasets include terrain, landuse, soil type, annual deep soil temperature, monthly vegetation fraction, maximum snow albedo, monthly albedo, and slope data. These datasets acts as initial terrain and boundary conditions representing the region under study.

4.1.1.4. Data of Interest

Landuse Landcover Data

The landuse landcover data from multi-temporal AWiFS at a scale of 1:250000 is prepared under **National Bureau of Soil Survey and Land Use Planning (NBSS & LUP)** for year 2008-09. It had 19 classes comprising of Kharif only, Rabi only, Zaid only, Double Cropped/Triple Cropped, Plantation, Fallow land, Evergreen/ Semi evergreen, Deciduous, Shrub/Degraded/ Scrub, Littoral swamp/ Mangrove/ Fresh water swamp, Grassland & Grazing land, Other wasteland, Guilled/ Ravines, Scrub land, Water bodies, Shifting cultivation areas, Snow cover/ Glacial/ Cloud, Built up land (Urban/ Rural) and Rann area. This data is obtained for the study.

Digital Elevation Data

The digital elevation is downloaded from http://earthexplorer.usgs.gov/. SRTM (Shuttle Radar Topography Mission) data of 3 arc-second (approximately 90-meter) medium resolution elevation data is used in the study.

Leaf Area Index

MODIS (Moderate Resolution Imaging Spectro-radiometer) Leaf Area Index at 1km resolution at a frequency of 8 day interval is downloaded for months from October, 2008 to April, 2009. The website http://earthexplorer.usgs.gov/ is used to download the data.

4.1.2. Data requirement for DSSAT crop model

DSSAT as mentioned earlier is a collection of various crop models serving as a single platform with common input and output files. CERES-Wheat is the model used to simulate the wheat growth. For its run it requires minimal dataset that are mentioned below.

4.1.2.1. Weather Data

The minimum required weather variables are Minimum and Maximum Temperature (°C), Solar Radiation (MJ/m^2) and Precipitation (mm) at daily time scale. The relative humidity (percentage) and wind speed (km/hr) if available can also be used but both are optional. It also requires latitude, longitude and elevation information. The sources of these data used in the present study are:

NCEP dataset

The National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) was completed over the 32-year period of 1979 through 2010. The CFSR was designed and executed as a global, high resolution, coupled atmosphere-ocean-land surface-sea ice system to provide the best estimate of the state of these coupled domains over this period. It is a gridded dataset at a resolution of about 25 kms. It gives minimum temperature, maximum temperature, solar radiation, precipitation, relative humidity and wind speed at daily frequency. These data is downloaded from October, 2008 to April, 2009 from http://globalweather.tamu.edu/.

WRF model's output

The forecasted weather conditions generated from WRF model at various time scales at 10 km resolution is used as another source. The forecasts are obtained at lead times of 7 days, 15 days, 30 days and 45 days.

Automatic Weather Station Data

The AWS (Automatic Weather Station) Data is downloaded from MOSDAC (Meteorological and Oceanographic Satellite Data Archival Centre) website http://www.mosdac.gov.in/. The data is downloaded for a period of 2008-2009 for 16 stations of Punjab. It includes temperature, precipitation, wind speed, wind direction and relative humidity on hourly basis and daily sunshine hours.

4.1.2.2. ***Soil Data***

The soil resource database of India was produced based the soil map at 1:1 m published by NBSS&LUP was used. The soil attribute database on map unit id, soil depth, drainage, particle size, slope, erosion, surface stoniness, flooding, calcareousness, salinity and sodicity data was compiled and codified as per OGC standard and extended legend was prepared as per the INARIS data structure. The other attribute database like SRM map units, pedon no., colour, surface texture, soil temperature regime, parent material, land (surface) form, organic carbon (OC), cation, exchange capacity (CEC), soil reaction (pH) and mineralogy were compiled at respective regional centre from SRM data (1:250,000 scale) and was provided to enter in the main database as per the INARIS data structure. The soil map is thus acquired from this project.

The depth wise soil status is collected from literatures *(Sehgal, J.L., 1974; Murthy et al., 1982; Verma et al., 1995; Verma et al., 2005; Buttar et al., 2006)* referred to as benchmark pedons, in association with its soil characteristics.

4.1.2.3. ***Management Data***

The management data are taken from similar previous studies. The parameters derived are irrigation times and dates, depth of irrigation, type of irrigation, type, amount, date of fertilizer application, sowing depth, row spacing of plants, plant population, etc., *(Buttar et al., 2006; Timsina et al., 2008; Balwinder et al., 2010*; *Balwinder et al., 2011)* .

4.1.2.4. ***Crop Cultivar Data***

The irrigated timely sown popular variety PBW 343 is used as the crop cultivar for the same reason considered in the above case. It is double dwarf variety with an average plant height of 100 cm. It tillers profusely and has stiff straw thus resistant to lodging. The ears are dense, fully bearded with white smooth glumes. Its grains are bold, amber hard and lustrous. It is resistant to yellow and brown rusts, susceptible to Karnal bunt and loose smut diseases. It is a long duration variety and matures in about 155 days. On research farm trials its yield is 23.5 quintals per acre and on farmer's field trails it yielded 22.3 quintal per acre. The Growth degree day requirements, vernalization sensitivity, critical photoperiod and other ancillary information are referred from previous studies *(Singh et. al., 2010; Hari Ram et al., 2012).*

*4.1.2.5. **Sowing Date and Crop Acreage***

Eight day surface reflectance data of MODIS is downloaded at a resolution of 500 meters from October, 2008 to January, 2009 for crop acreage estimation and sowing date assessment. Source: http://earthexplorer.usgs.gov/.

4.1.3. Validation Data Requirements

4.1.3.1. *Weather Data*

AWS data

The ISRO-AWS in 16 locations of Punjab with seven weather variables (as mentioned in section 4.1.2.a) is used to validate the forecasted weather outputs from WRF.

Global Weather Data

The weather station data downloadable at Global Summary of a day by NOAA (National Ocean and Atmospheric Administration) as a global compilation is used for validation at a few sites in Haryana.http://www.ncdc.noaa.gov/cgi-bin/res40.pl?page=climvisgsod.html

Solar Radiation

The Solar Radiation data from SUNY model is used to validate the solar radiation output from WRF model. SUNY model produces estimates of global and direct irradiance at hourly intervals on the 10-km grid for all of India. The data are produced using visible images from a Meteosat satellite. The images from the satellite are produced 7 minutes before each hour, GMT. Thus, the model produces the "instantaneous" values at 7 minutes before the hour. These values are then shifted to represent the average value for the previous hour. From http://rredc.nrel.gov/solar/new_data/India/nearestcell.cgi web address.

4.1.3.2. *Yield Data*

District-wise actual wheat yield data is obtained for the season 2008-2009 from National Food Security Mission (NFSM) at http://nfsm.gov.in/NfsmMIS/rpt/apy.aspx.

4.1.3.3. ***LAI Data***

As mentioned in section 4.1.1.4 the leaf area index is used to calibrate and validate the models’ simulated leaf area index on spatial scale.

4.2. Software Used

4.2.1. Software

ArcGIS 10, ArcGIS 9.3, ERADAS version 9.2, ENVI 4.5 are used to collectively process the images, to help in data preparation and do spatial analysis of the outputs.

4.2.2. Models

WRF model version 3.4.1 is used for weather forecasting along with its pre-processing (WPS) and post-processing (ARW Post) tools compatible with LINUX platform. DSSAT version 4, Windows platform is used to run the crop simulation in spatial extent.

4.2.3. Programming Languages

Python 2.5 scripting language is used to prepare multiple input files, process and validate multiple outputs. GrADS (Graphical Analysis and Display System) is used to process and extract the outputs from WRF. FORTRAN (FORmula TRANslation) is used to program and process multiple files in LINUX platform.

4.3. Methodology:

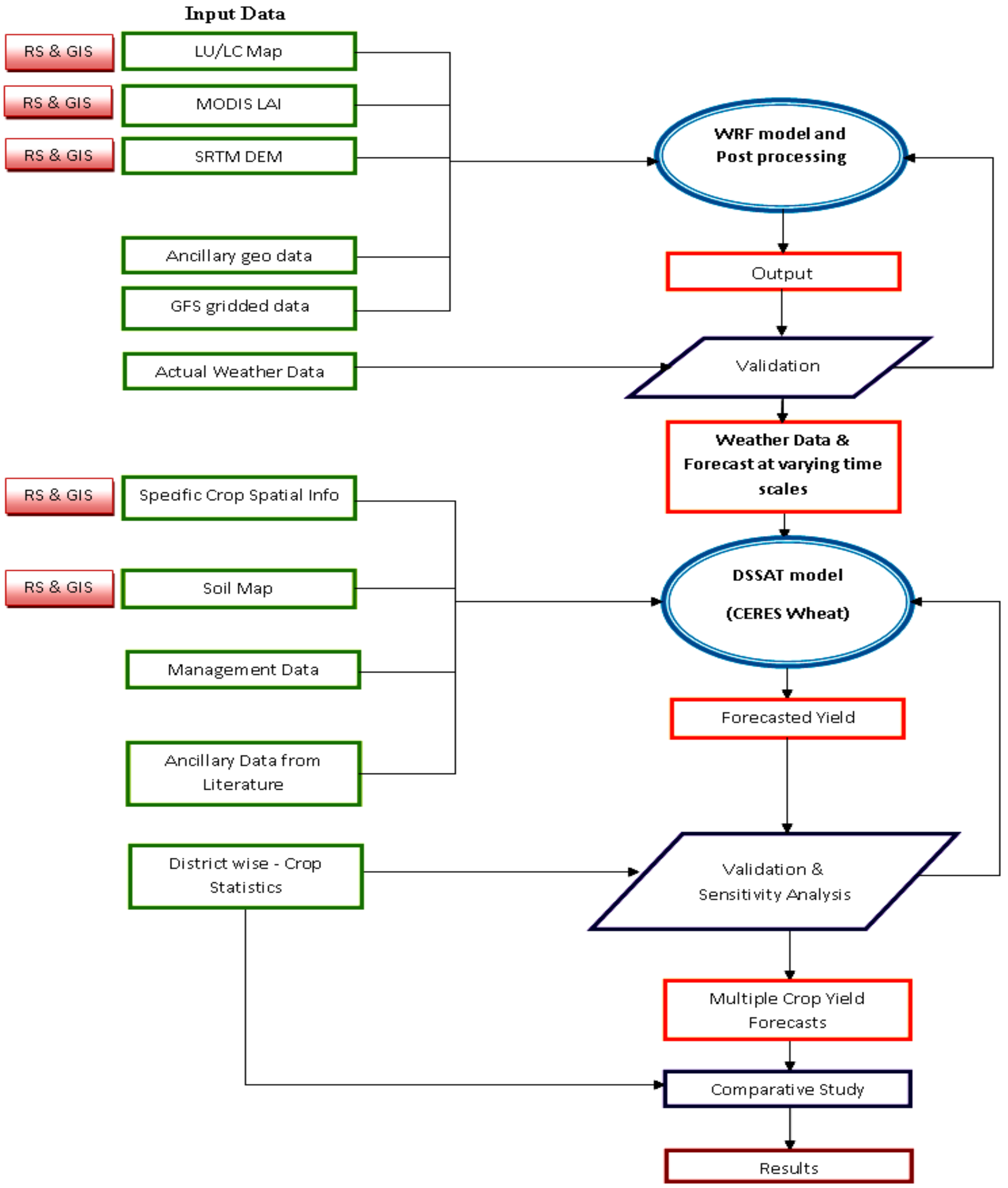


Fig.4.1-Simplified flowchart of the methodology adapted for the study

4.3.1. Weather Forecasts

The forecasts of the weather at different time scales is generated using Global-WRF updated with certain critical remote sensing input datasets. This section explains the methods involved in creating the inputs, simulation experiment of the model and the validation strategy concerned with assessing the performance.

4.3.1.1. Preparing the Input Data of Interest

The model's basic requirements for a run are terrestrial datasets, initial and lateral boundary condition data from global circulation models and lower boundary data. The lateral boundary conditions consist of later times gridded info at model points in a zone i.e. five points wide around the domain. The initial conditions are the present condition of the weather over the region. Both these data can be obtained from global circulation model's output. GFS data is downloaded for the dates the simulation starts. Lower boundary data like the SST data are not required by the WRF model, but when running very long simulations, it is beneficial to have updating SST during the model run. The terrestrial boundary conditions are prepared and made available at various resolutions (refer section 4.1.1).

One of the study's objectives is its interest to change the critical inputs in the terrestrial dataset and test the degree of sensitivity of the model to those changes. For this purpose the terrain data and land use data is exploited. Also, as an addition leaf area index dataset is made dynamic on monthly time scale in the model. USGS land use/land cover dataset available with WRF from geog dataset is of coarser resolution and generated during April, 1992 to March, 1993. AWiFS is used to generate land use/land cover at 58 meter resolution and for the year 2008-2009. SRTM 90 m digital elevation model is used over the existing digital elevation model at 1 km resolution. This led to better representation of terrain especially variable terrain regions. Leaf Area Index which in the model is calculated from look up table method based on the land use classification is replaced with monthly Leaf Area Index derived from MODIS at 1 km resolution. The difference the datasets at models resolution is explained in the results section.

The input data are downloaded to cover an area that is larger than the model's domain area so as to avoid the artificial boundary problem. The DEM is checked for being void and processed if necessary. The landuse landcover obtained from AWiFS is recoded to match the 24 classes of USGS. This is done so that the classes will take advantage of the vegetation parameters like albedo, roughness length, green vegetation fraction, stomatal resistance that are standardized for each class of the USGS. The monthly LAI (1 km resolution) is generated as a maximum composite from three to four images that will be available per month in eight day frequency. The LAI is then stacked to represent the whole year. The images that are produced are tiled and converted to ASCII with the help of python programming. Tiling is done because the geog binary format in which the model reads the input data has some limitations in the size of the rows and columns in a single parcel. Later these ASCII files are transformed to geog binary format (format of WRF) in projection of regular_ll (Geographic latlon) with the help of FORTRAN programming. The index file for each dataset is prepared and the GEOGRID.TBL is edited to intake the new datasets. For monthly LAI the WRF model is compiled specifically by adding some code to the initialization routine and while running the model the rdlai2d flag is enabled. One has to be very careful of the interpolation technique that is used to interpolate the data by the model according to the model's resolution, since it may alter the data representation of the modified run.

4.3.1.2. Model Specification

The forecast model used in this study is the Weather Research and Forecasting (WRF) *(Skamarock et al., 2008)* Model version 3.4.1 (http://www.wrf-model.org). This mesoscale numerical model is designed to serve both operational forecasting and atmospheric needs. Here in this study WRF-ARW (Advanced Research WRF) core is used. It uses Arakawa C-grid staggering for the horizontal grid and a fully compressible non-hydrostatic (with hydrostatic option) system of equations. Mass-based terrain following hydrostatic pressure with vertical grid stretching is followed for the vertical grid. The time-split integration uses the third-order Runge-Kutta scheme with a smaller time step for acoustic and gravity wave models. It is a limited-area, non-hydrostatic primitive equation model with multiple options for various physical parameterization schemes. Physics options used in this study includes the Kain-Fritsch *(Kain and Fritsch, 1990, 1993)* cumulus parameterization scheme and the Purdue Lin et al. scheme for microphysics. The planetary boundary layer is parameterized using the Yonsei University (YSU) planetary boundary layer scheme *(Hong and Dudhia, 2003; Hong and Pan, 1996)* and for soil model, the multi-layer Noah land surface model (LSM) is used. The long-wave radiation scheme is based on the rapid radiative transfer model (RRTM), and the short-wave radiation is based on Dudhia *(1989)*.

4.3.1.3. WRF Process Description

WRF can be thought of as being composed of three layers. One layer is largely driven by the GCM, another layer builds on some locally specific data (DEM, LU/LC, Soil, and LAI) and the third layer uses its own physics based equations to resolve the model based on data from the other two. The results are comparatively local predictions that are informed by both local specifics and global models. The results are comparatively local predictions that are informed by both local specifics and global models. The WRF Modelling System consists of these major programs:

4.3.1.3.1. The WRF Pre-processing System (WPS)

The WPS consists of three independent programs: *geogrid***,** *ungrib*, and *metgrid*. Each of the programs performs one stage of the preparation: *geogrid* defines model domains and interpolates static terrestrial data to the grids, it takes support from GEOGRID.TBL in reading the inputs; *ungrib* extracts meteorological fields from GRIB-formatted files; it makes use of the Vtable to read the input. The Vtable has to be specified by the user depending on the data from the global circulation models and *metgrid* horizontally interpolates the meteorological fields extracted by ungrib to the model grids defined by geogrid using the METGRID.TBL.

4.3.1.3.2. ARW dynamic solver

This is the key component of the modelling system, which is composed of several initialization programs for idealized, and real-data simulations, and the numerical integration program. The output of WPS is met_em.* files. The real.exe will run with this as input, vertically interpolating meteorological fields to WRF eta levels. The output of this are wrfinput_d01 and wrfbdy_d01 files. These serves as input to WRF run along with the physics options and dynamics defined in the namelist.input file, gives the output data.

4.3.1.3.3. Post-processing & Visualization tools

The output data format is netCDF. netCDF stands for **Net**work **C**ommon **D**ata **F**orm. There are a number of visualization tools available to display WRF-ARW model ouput data. Currently the following post-processing utilities are supported: NCL, RIP4, ARWpost (converter to GrADS), WPP, and VAPOR. Here in this project GrADS (Grid Analysis and Display System) scripting is to be used to convert the output data in ASCII format to be further processed.

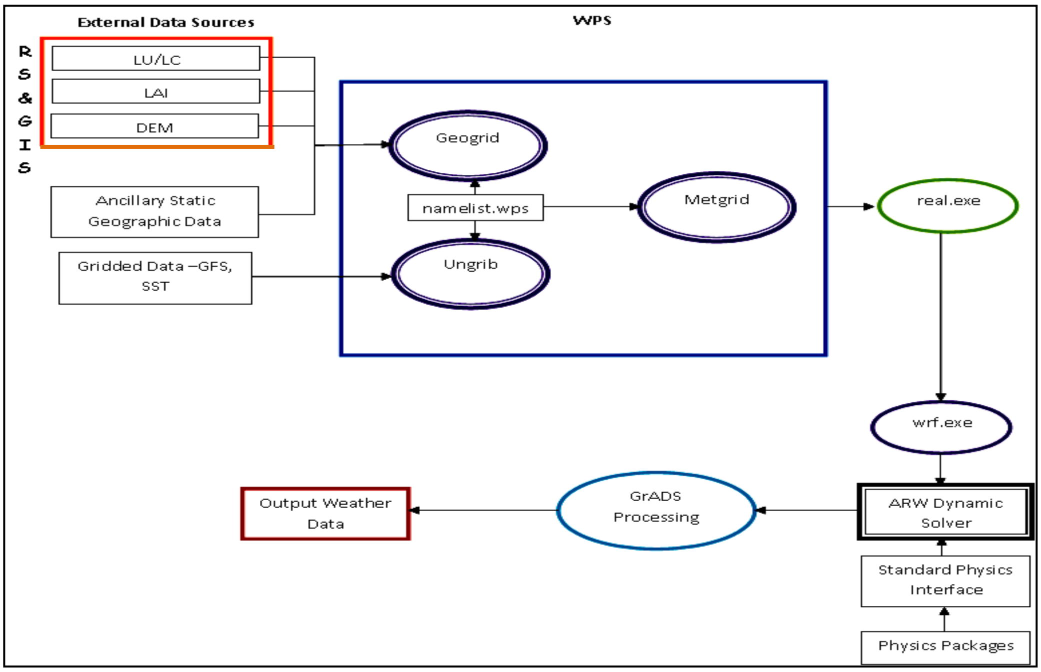


Fig.4.2-WRF Process

4.3.1.4. Impact Analysis of the model's performance

Two experiments (CNT: with existing datasets and EXP: with modified datasets) is run at 1km resolution for 12 hours from October 1, 2008, 1200 UTC with 36 vertical levels and domain consisting of 900 grid points with a temp step of 6 seconds. The run took a time length of 12 hours for each of the dataset with the processing capacity mentioned in Section 4.2.4. Both the runs were compared against each other and with actual data using statistical measures like RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percent Error) and Improvement factor (refer to Appendix for formula). The actual station data collected from ISRO AWS is used for validating the model's outputs at 15 station locations over Punjab.

4.3.1.5. Global run of the model

WRF is a limited area model which uses the boundary conditions for its domain from the global models, hence the forecast capability is reduced to the forecast lead time of the global models and the artificial boundaries between regions can create forecasting problems. Global WRF is adapted from community development at Cal Tech for planetary atmospheres. It is a functional system for nested non-hydrostatic global simulations *(Skamarock et al., 2008).* It forecasts the state of the atmosphere globally with a single initial file known as first guess (start GFS file) , the output of which acts as boundary condition and initial condition for the nest and can go up to regional level. Once the forecast is finished for first time step the feedback from the nests goes into the parent for the next time step, repeating the same process to get the forecast for that time step. This way short to long range forecasts can be generated from Global WRF for regional level.

In this study, Global WRF (ARW) is implemented for global domain with two nests at 1:5:5 ratios at three different levels. Two-way nesting is implemented where information exchange between the parent and the nest is bi-directional. The nest feedback impacts the coarse-grid domain's solution. The model has 36 vertical levels with the top of the model atmosphere located at 10 hPa. The forecast is done with the updated datasets for different time scales of 7 days, 15 days, 30 days and 45 days. The experiment is run at three levels the parent domain, first child domain and second child domain each of 250 km, 50 km and 10 km resolution respectively. The time step is 500 seconds. The SST update is enabled in the parent domain to have a realistic pattern of the influences of ocean in the atmospheric modelling for longer simulations.

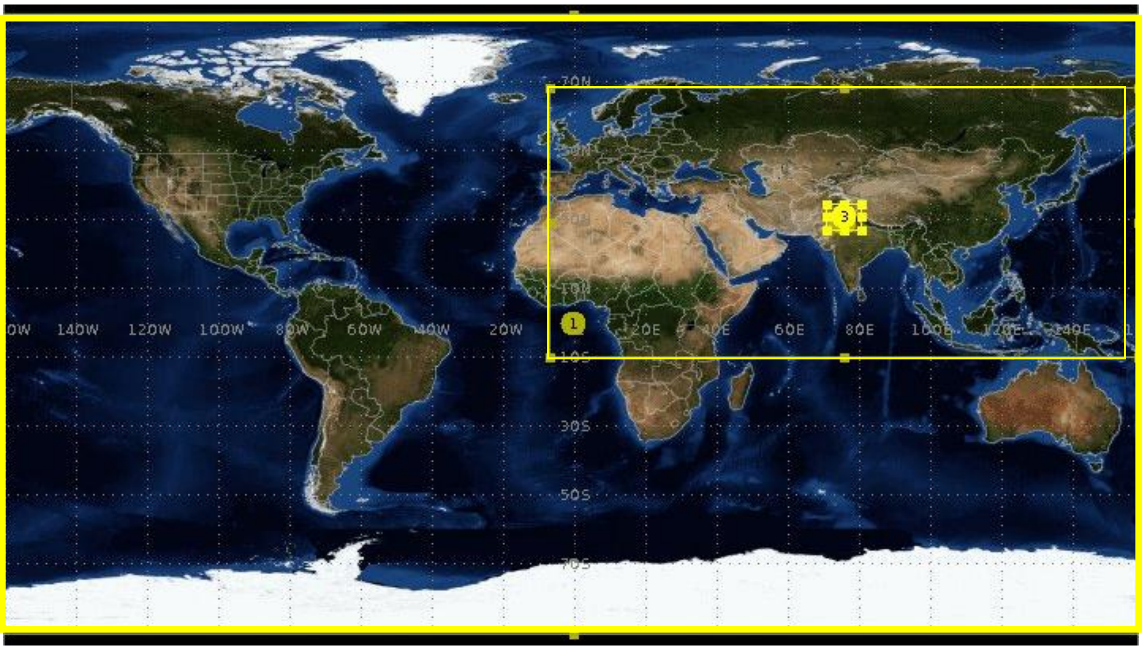


Fig.4.3-Nested Domains for the WRF model (the bigger box represents the global parent domain, first inner box represents the first child domain and the last inner box represents the second child domain)

4.3.1.6. Forecasting at various time scales

Thus, the forecast is generated at 4 lead times at a resolution of 10 km with daily frequency with Global WRF. The initial GFS file is downloaded for one single hour and date according to the start of simulation date for each experiment. April 17 is arrived as the majority harvest date for the study area by local knowledge and DSSAT model's calibration. According to this the specification is as mentioned below:

a. April, 10 to April, 17, 2009 – 7 days forecast.

b. April, 2 to April, 17, 2009 – 15 days forecast.

c. March, 18 to April, 17, 2009 – 30 days forecast.

d. March, 3 to April, 17, 2009 – 45 days forecast.

The variables of interest are Temperature derived from model's Temperature at 2 metre, Solar radiation from model's downward shortwave radiation, Relative Humidity, Wind speed derived from model's Wind speed at 2 metre and Precipitation by adding of model's convective precipitation and non-convective precipitation.

4.3.1.7. Validation

The forecasts for weather variables Temperature, Pressure, Relative Humidity, Wind speed and Precipitation are extracted at the location of the actual station data using GrADS scripting. The extracted point data are validated daily and hourly with the corresponding station data with the help of Python programming. The forecast skill of the model are evaluated with the statistical measures like RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percent Error) and Index of Agreement (refer to Appendix for formula). Solar radiation is validated with hourly radiation output of SUNY model (refer section 4.1.3.1)

4.3.2. Projection of the Crop Yield

The Crop Yield forecasting is the main objective of the study. The thus forecasted weather variables from the WRF model at daily time scale and 10km resolution is input into the crop simulation model along with other inputs to obtain a forecast on spatial extent across the regions of Punjab and Haryana. This section deals with the methods used to convert the data from WRF to DSSAT format, prepare other inputs in a spatial extent, run the model in a spatial mode, calibrating and sensitivity analysis and finally validation of the model's outputs.

4.3.2.1. Process of the DSSAT model

The Decision Support System for Agro-technology Transfer (DSSAT) Version is a software application program that comprises crop simulation models for over 28 crops (as of Version 4.5). The crop simulation models in DSSAT simulate growth, development and yield as a function of the soil-plant-atmosphere dynamics, and they have been used for many applications ranging from on-farm and precision management to regional assessments of the impact of climate variability and climate change. The driving variables are weather, soil, management parameters and cultivar specific genetic coefficients while the state parameters are LAI, biomass, yield. 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. Simulations are initiated either at planting or prior to planting through the simulation of a bare fallow period. These simulations are conducted at a daily step and, in some cases, at an hourly time step depending on the process and the crop model (refer Fig 4.3.3). At the end of the day the plant and soil water (as a function of transpiration), nitrogen and carbon balances are updated (as a function of photosynthesis), as well as the crop's vegetative and reproductive development stage (as a function of growing degree days). Thus, five processes are given detailed attention. They are

- Phenological development, especially as it is affected by genetics and weather.
- Extension growth of leaves, stems, and roots.
- Biomass accumulation and partitioning, especially reproductive organs.
- Soil water balance and water use by the crop.
- Soil nitrogen transformations, uptake by the crop, and partitioning among plant parts.

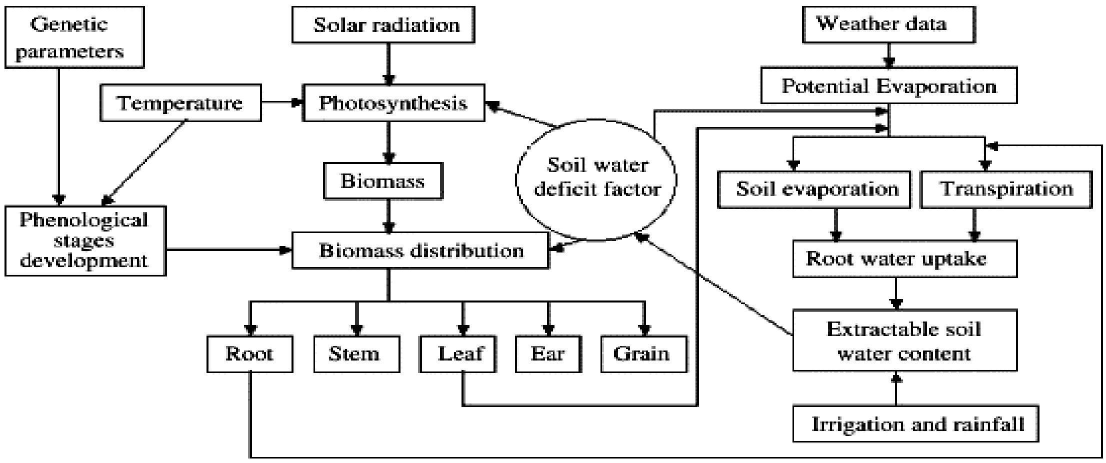


Fig.4.4-Conceptual diagram for wheat growth and yield formation and their influencing factors in the DSSAT-CERES wheat model (Yonghui Yang et al., 2006)

The DSSAT is enabled for spatial mode i.e. they allow spatial analysis. The scenarios may represent contiguous polygons in coverage or map of an area is, as far as the models are concerned, irrelevant. For this reason, the "spatial" capabilities of the DSSAT are, in sense, very limited. Thus the spatial mode is achieved by two parts. First is to create a values file that contains the attributes for each distinct polygon under study; second is to take those values file and to create all or part of an experiment file.

4.3.2.2. Model Calibration –Point basis

CERES model is based on black box approach and therefore cannot be easily adapted or modified to the local conditions. Thus manual calibration of the model by altering the values of the parameters to make it effective for the local study is a must. The actual station data is used to calibrate the model. Three stations are chosen to calibrate the yield. These station locations are selected to have low, medium and high yields, so that the model may get calibrated to the extreme conditions also. The initial inputs obtained from the literatures are tried in the model. According to the output yield, the input variables were adjusted. This is done until the outputs of the three locations are almost fitting the actual yield.

4.3.2.3. Model Calibration –Spatial Basis

Calibration as told earlier is done for three levels of yield in station basis. But here since we would like to do a spatial run, calibration has to be done on a spatial extent to get agreeing results on a spatial scale. It is for this purpose MODIS LAI is being used.

The reserves weight starts accumulating slowly after the emergence of the crop. Its accumulation attains maximum at stages from double ridge formation to anthesis, after anthesis the reserves weight is slowly converted to the grain weight along with a little accumulation on daily basis thereafter. The grain weight accumulation rate reaches a maximum after which the rate starts slowing down and attains stability thus making the crop reach its maturity. The reserves weight and grain weight are taken as a proxy to understand the system. While reserves weight is a function derived from Reserves concentration of CH2O, temperature, PAR conversion efficiency; the grain weight from number of grains/m2, grain unit dry weight, and a set of other variables. The importance of reserves weight on the final yield is demonstrated by *Esmaeilpour-Jahromi et al., 2012.*

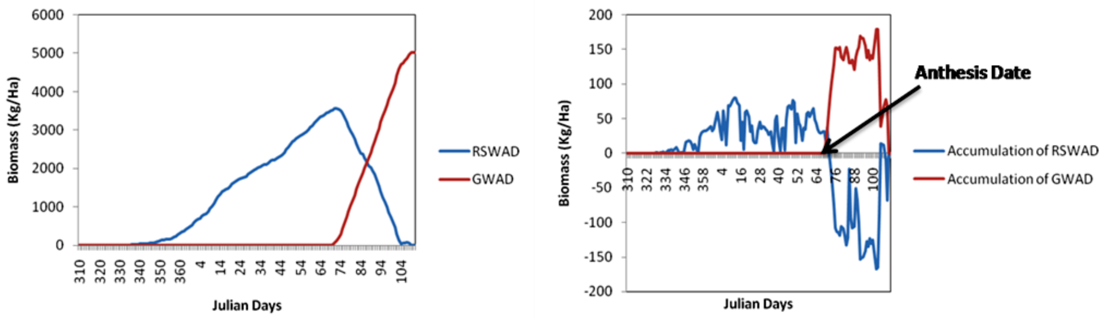


Fig.4.5-(a) The left figure explaining the relationship between Reserves weight (RSWAD) and Grain weight (GWAD) (b) The right figure explaining the rate of accumulation of RSWAD and GWAD

Now this understanding would help to explain the behavior of the model. LAI is indirect representation of the progress of plants life cycle. Fig 4.3 shows that LAI and reserves weight are almost directly proportional, that is, the processes that is responsible for increase in reserves weight also influences the measure of LAI. Thus LAI can be considered to calibrate the model spatially. Though MODIS LAI has some errors this kind of methodology is used world-wide as there is no other effective means to achieve spatial calibration.

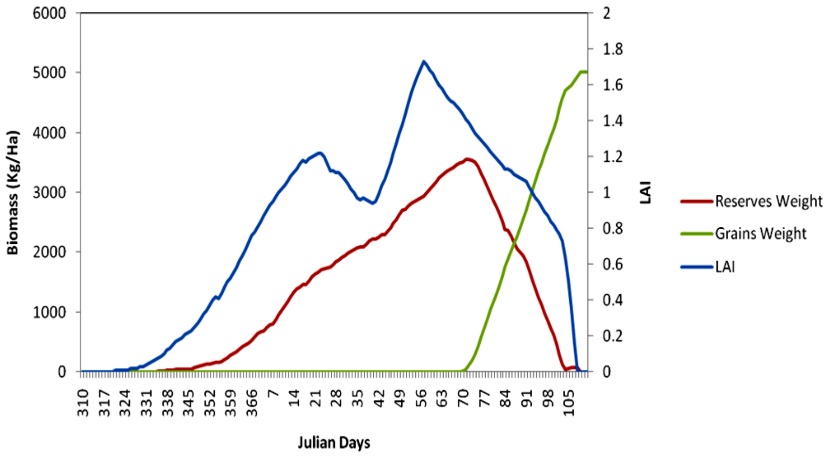


Fig.4.6-Significance of LAI with respect to reserves weight and grains weight

4.3.2.4. Preparation of the input files

Here as the spatial study is addressed remote sensing data is used for sowing date estimation and crop acreage assessment. This section explains the preparation of the inputs on a spatial basis.

4.3.2.4.1. Grid Points generation

The spatial mode available with DSSAT is not fully in spatial sense. Accordingly the representation, each polygon is a point with all the details stored as attributes of the point also having locational information and the area under the polygon. Here in this project the aim is to study the regional simulation of crop yield at a resolution of 10 km. Thus, the grid points are generated at a distance of 10 km from each other. The grid cell of resolution 10 km each forms the polygon that the point is representing. Every attribute of that particular polygon is written to the point. This is created with the help of ArcGIS and available as a shapefile. Thus for the study area 1040 grid points is generated.

4.3.2.4.2. Weather Data

NCEP Gridded Weather Data

As mentioned in Input Data section the NCEP data at a grid resolution is downloaded at a spatial resolution of 25 km and temporal resolution of a day. The Kriging (ordinary) interpolation with semivariogram type, Spherical is used to interpolate the points and then extracted to 10 km grid points. Then a separate file for each grid point is generated with daily weather data from October, 2008 to April, 2009. The whole process is achieved with the help of python programming.

Gridded Weather from WRF

The daily weather variables like minimum temperature, maximum temperature, solar radiation, that is necessary for the run is extracted from the gridded WRF output at the grid points' location with the help of GrADS scripting.

These weather variables at various time leads are then combined with the NCEP gridded data available at the same location and the database for the Rabi season (2008-2009) is created for each grid point. They are then converted to test files with .WTH extension (DSSAT format for daily weather files) and header information as mentioned in DSSAT 3.5 manual. This is also accomplished with Python programming.

Creation of actual daily weather data for DSSAT

The actual station data are also used in the model for calibration and sensitivity analysis. The hourly data is first converted to daily data for each station. Then database is created with these daily weather variables for each station. Later the database is written in text format as required by DSSAT. All these steps are automatically done with python programming.

The forecasted weather from WRF is also combined with the actual weather data at different lead times creating an ensemble at point level, to study the effects of the forecasts in the simulation.

4.3.2.4.3. Soil Data

The information on soil in a spatial domain was obtained from soil map prepared by NBSSLUP at 1:250000 scale. The soil data obtained (refer section 4.1.2.4) is extracted to each grid point. The parameters other than basic ones are obtained from literatures and correspondence made with the drainage and soil depth. Thus the soil database for each grid point is created. This is then converted to a single text file with .SOL (DSSAT format for soil files) as per the alignments mentioned in the DSSAT 3.5 manual Volume 2. Again the process is completed with python programming.

4.3.2.4.4. Cultivar Data

Since the model is run in optimal to semi-optimal conditions, the cultivar is generalised over the study area (which is also supported by section 3.3). The variety PBW 343 is very popular variety in the study area and ample studies has conducted with field experiments and the critical genetic coefficients are computed. The standard plant height is set as 94.4 cm. The critical parameters for normal yield arrived after calibration is listed in table 4.1.

Table.4.1. The Genetic parameters to the model

Growth and Developmental Aspects of Wheat Crop	Genetic Coefficients
	PBW-343
Development Aspects	
Optimum Vernalizing Temp (P1V) (Days**)**	20
Critical Photoperiod (P1D) (%)	80
Grain-filling duration coefficient(P5) (°C.d)	650
Growth Aspects	
Kernel number coefficient(G1) (#/g)	23
Kernel size coefficient(G2) (mg)	45
Single tiller weight (G3) (g)	1.5
Tip leaf appearance interval(PHINT) (°C.d)	95
PAR conversion to dm ratio (g/MJ)	2.94

4.3.2.4.5. Management Data

Planting Details

The planting method is through seed sowing, planting distribution is row wise, plant population is 50 plants/ m^2 with a row spacing of 23 cm and sowing depth of 6 cm.

Irrigation and Water Management

Irrigation is by furrow method and irrigated six times in throughout the season. The first irrigation is applied at the time of crown root initiation (CRI) stage. In timely sown wheat, first irrigation is given between 20-25 days after sowing (DAS). The second irrigation is applied between 40-45 DAS, which coincides with tillering stage. Third irrigation is provided at late jointing stage between 65-75 DAS. The fourth irrigation is given at the flowering stage between 90-95 DAS. The fifth and sixth irrigations are applied at milking stage (110-115 DAS) and dough stage (120-125 DAS) respectively.

Fertilizer Management

The cultivar requires Nitrogen of 110 kg/ha, Phosphorous amounting to 50 kg/ha and the Potassium required is 40 kg/ha. Urea is applied at 2 splits one at the time of sowing and one at the time of first irrigation. Fertilizers of Phosphorous and potassium are applied at the time of sowing.

The management practices are assumed to follow the recommendations throughout the simulation extent which may not exist but to simplify the complexity of the study.

4.3.2.4.6. Remotely sensed information

Wheat area distribution

The wheat crop is classified by considering the growth profile of each pixel. Enhanced vegetation index is calculated from 8-day composite MODIS reflectance data downloaded for the Rabi season of 2008-09 by using formula:

$$EVI = G \times \frac{(NIR - RED)}{(NIR + C1 \times RED - C2 \times Blue + L)} \quad \textbf{-- (1)}$$

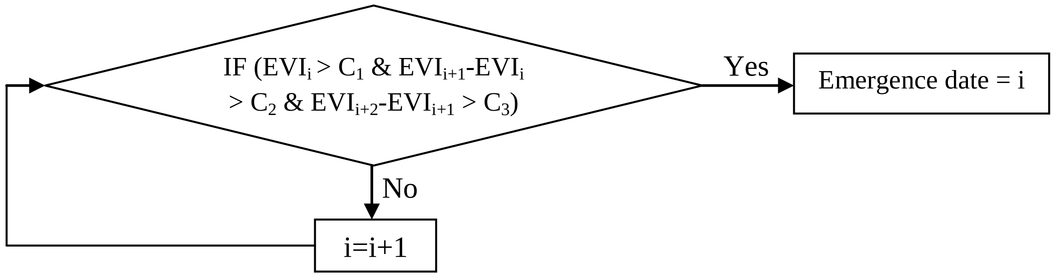
where NIR/red/blue are atmospherically-corrected or partially atmosphere corrected (Rayleigh and ozone absorption) surface reflectance, L is the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy, and C1, C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the MODIS-EVI algorithm are; L=1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5.

The EVI thus computed is stacked date-wise from October, 2008 to April, 2009 thus generating profile for each pixel. Knowledge based classification is done on this stacked image that if the slope of the profile is increasing till mid of February from somewhere in October, November or December then the pixel belongs to wheat crop. This way the whole image is classified. The efficiency of this output is discussed in the next chapter.

Sowing Date

Sowing Date is an important parameter to the model. Remote Sensing technique is attempted to arrive at the majority sowing date for the region. *Vyas et al., 2013* in a recent study tried to derive regional pattern of sowing dates from multitemporal data. Similar methodology is followed here.

The EVI computed is stacked date-wise from October to January, 2009. Non- wheat pixels are eliminated from the previous method's output. The profile for each wheat pixel is thus generated. Below mentioned algorithm is executed for every pixel of the image:



where EVI_i is the pixel value of the present date, EVI_{i+1} is the pixel value of the consecutive second date, EVI_{i+2} is the pixel value of the consecutive third date, C_1 is the EVI threshold (decided after thorough examination of the study area's wheat pixels) and C_2, $C_3 > 0$. i is incremented until end of December.

The explanation of the algorithm is that if the slope of the profile is increasing then the start point of the slope is the emergence date. The sowing date is measured subtracting 7 days from the emergence date, since emergence is considered to start one week after sowing. November, 6 is arrived as sowing date used in the model since majority of the wheat pixels belonged to this date. The results of this output are discussed in the next chapter.

4.3.2.5. Design of spatial simulation experiment

The grid points were segregated to high, medium and low yield groups by comparing it to district-wise yield data. These segregated groups used separate input data especially in terms of management practises and genetic coefficients that is arrived after calibration. The methods used for various functions are listed below

a. Light interception – Exponential with LAI

b. Evaporation – FAO-Penman

c. Infiltration – Soil Conservation Service Routines

d. Photosynthesis – Canopy Photosynthesis Response Curve

The spatial FileX (experimental files in DSSAT) are created for the segregated grid points separately and associated with weather and soil databases. The management practises and the simulation controls are mentioned in the experimental file itself. This generation is also done with the help of python programming. The model is run and the outputs are obtained. The daily growth file, plant growth summary file, daily weather file are some of the outputs that are vital for the study. The same procedure is repeated across various scenarios of weather data.

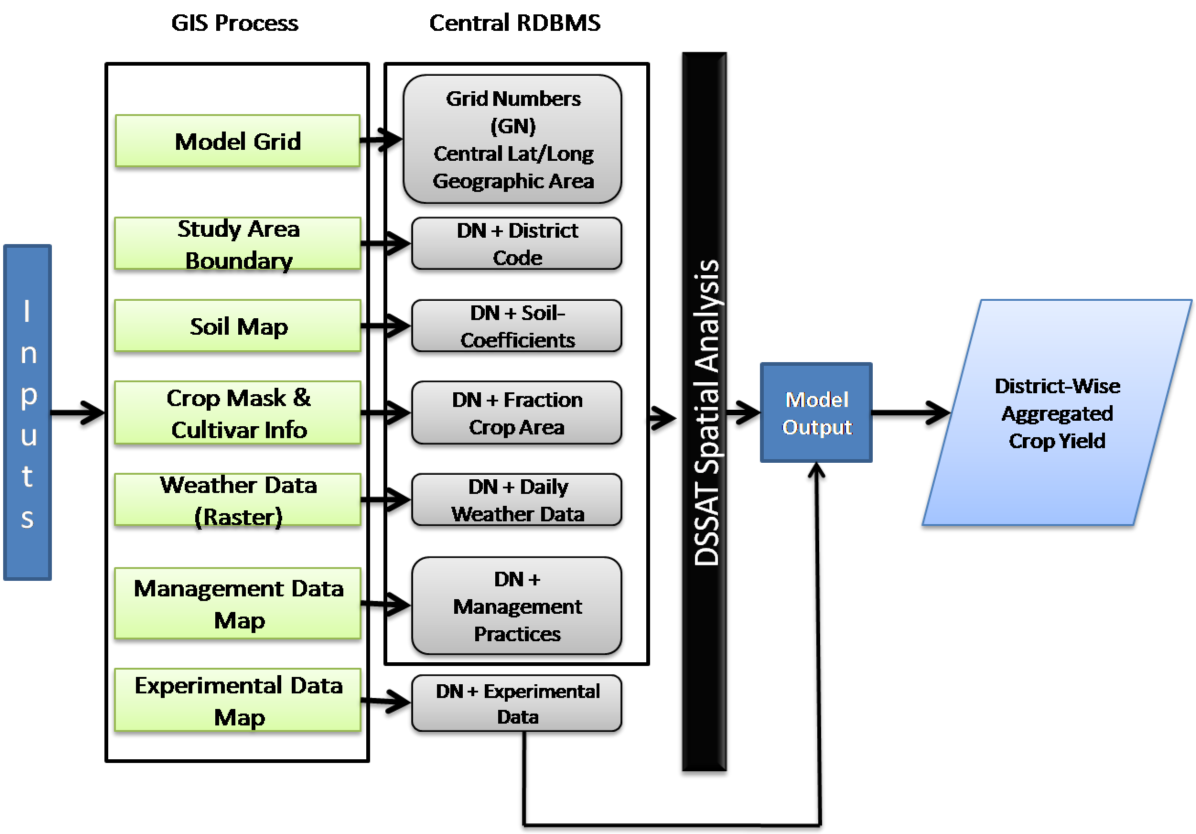


Fig.4.7-Methodology for gridded run of DSSAT

4.3.2.6. Sensitivity Analysis

The sensitivity analysis is done to just analyse the critical parameters to the model. It is one obvious fact that the model is sensitive to weather parameters. The model's sensitivity to weather parameters is to be quantified in the results chapter. Other than that, the sowing date has quantifiable influence over the model's performance. The soil type, irrigation schedules, fertilizer amount is known widely to influence the model's final output, while they are not tested. The results of sensitivity analysis are discussed in the next chapter.

4.3.2.7. Generating multiple forecasts

Different sets of the forecasts are generated with varying sources of the weather data. Below the forecasts are described and coded for future mentioning and comparison.

4.3.2.7.1. *Regional gridded yield forecast*

The forecast on a spatial basis is obtained from gridded weather datasets created by the numerical weather prediction models.

- F1- Full set of NCEP reanalysis weather data (estimate)
- F2- NCEP weather data + 7 days WRF forecast
- F3- NCEP weather data + 15 days WRF forecast
- F4- NCEP weather data + 30 days WRF forecast
- F5- NCEP weather data + 45 days WRF forecast

4.3.2.7.2. *District level-weather station based Forecast*

The actual weather data from AWS stations and routine observatories are also used in combination with weather forecast of corresponding station grid at different lead-time. Weather forecast data tested to see how early yield forecast can be made with reasonable accuracy. The WRF forecast is extracted for the particular station’s location.

- F6- Actual Station Data+7 days WRF forecast
- F7- Actual Station Data+15 days WRF forecast
- F8- Actual Station Data+30 days WRF forecast
- F9- Actual Station Data+45 days WRF forecast
- CNT_YD- Actual Station Data (Controlled Run for Crop Yield)

4.3.2.8. Validation of crop yield district-wise and spatially

Crop statistics comprising actual yield of wheat at district level obtained from statistics at a glance, an online website of Dept. of Agriculture (Ministry of agriculture & Cooperation). The validation of the yield is done at district level for both station derived yield (point level) and the regional level gridded forecast. MODIS LAI is also used to validate the gridded forecasts at spatial level.

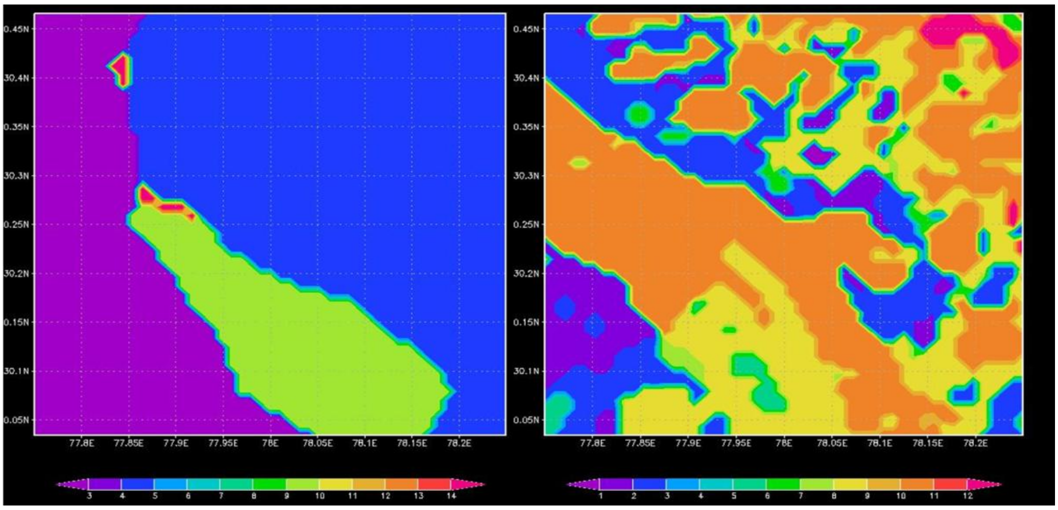
Chapter 5

RESULTS & DISCUSSIONS

5.1.Representation of land surface boundary in WRF

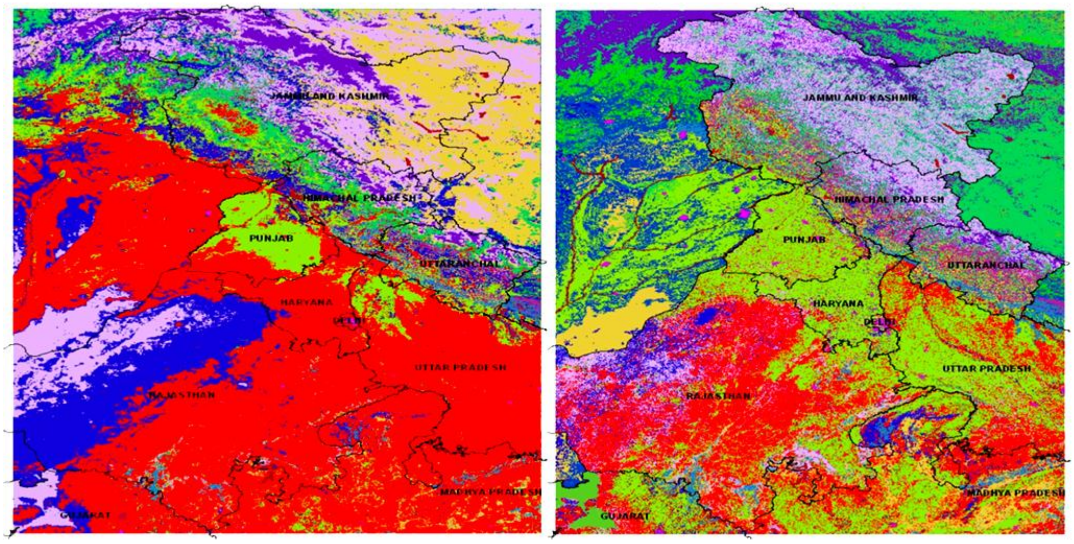
5.1.1. Landuse/Landcover

As mentioned in the methodology, the information on landuse categories as used in CNT is derived using coarse resolution satellite data in 80s and may not be representative for current condition. Fig 5.2 illustrates this difference between the USGS (default) dataset and AWiFS dataset. The boundaries outside India is the same i.e. USGS dataset. The changes are prominent over the Indo-Gangetic plains where the increased irrigation practices have considerably resulted in up gradation of the class from Dryland crop pasture to Irrigated crop pasture over the years. This is well captured by AWiFS dataset while the USGS doesn’t represent this. The increased area under barren land in Rajasthan is also reasonably well represented in the updated AWiFS dataset. Overall urbanisation has gone up. This is well captured in the AWiFS dataset. Urban part of Delhi has gone up and also places surrounding it in Haryana and Uttar Pradesh has been urbanised. Punjab and Haryana has increased urban spots that are visible in the updated AWiFS dataset. The snow cover over the North of Jammu and Kashmir has increased a little, while notable decline in barren land. The forest area over the Himachal Pradesh and Uttrakhand is altered slightly; this change is prominent near Shivalik ranges. Thus, this shows that updated LULC information from medium resolution AWIFS could capture some important details of restructured heterogeneity in land cover and led to the realistic representation of the landuse landcover data at models’ resolution as demonstrated in Fig 5.1.



(a) Landuse landcover categories in USGS dataset (b) Landuse landcover categories in AWiFS dataset

Fig.5.1-Part of the study area showing large variation in landuse landcover at models' resolution

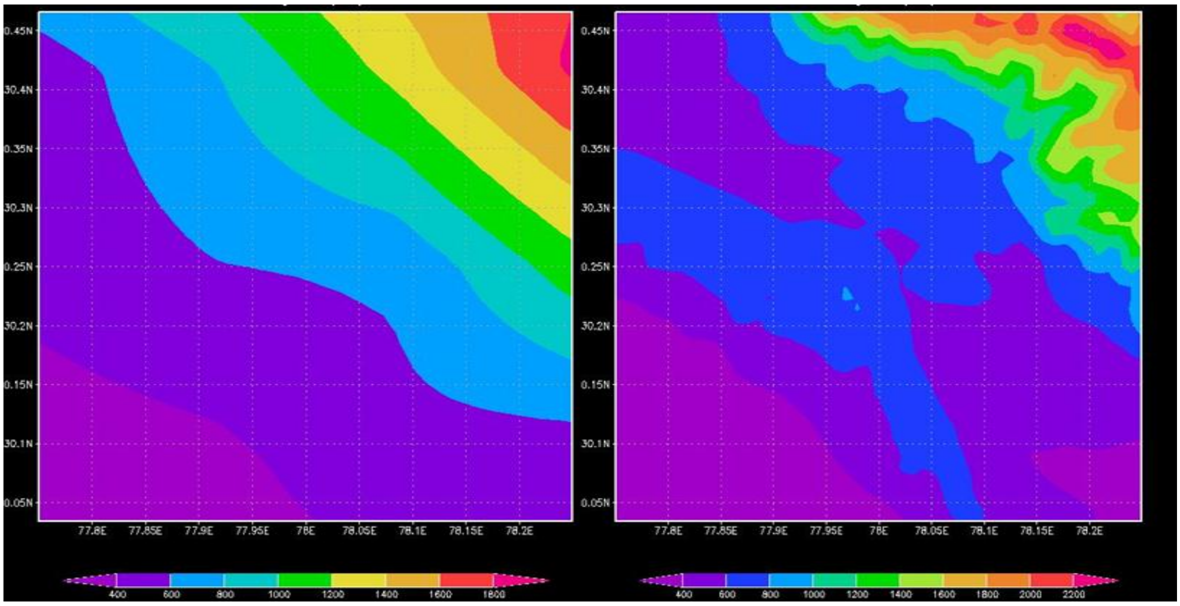


(a) Landuse landcover categories in USGS dataset (b) Landuse landcover categories in AWiFS dataset

Fig.5.2-Dominant landuse landcover categories

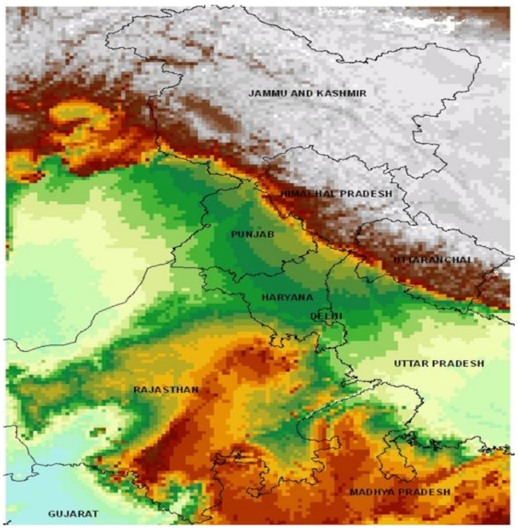
5.1.2. Terrain and topography

The terrain is represented in a finer manner with the updated high resolution Digital Elevation Model. The distinct differences are exhibited at areas where the terrain is complex.For example the Fig 5.3 represents the Uttrakhand state. The earlier DEM shows a gradual increase in the elevation while the modified DEM captures the heterogeneity in elevation particularly over Shivalik ranges; the valley in between (Dehradun and adjacent region) and the increasing elevation towards the Himalayas which is not prominent in the former. Fig 5.4 gives an overall comparison of the dataset for the study area. A smooth effect is shown in the updated dataset. The need for smoothening is explained by *Walker et al., 1994*. Even when the model's resolution is coarser, appropriate smoothening on finer resolution DEM should be done explicitly so that the complexity in the rough terrain will not be lost.

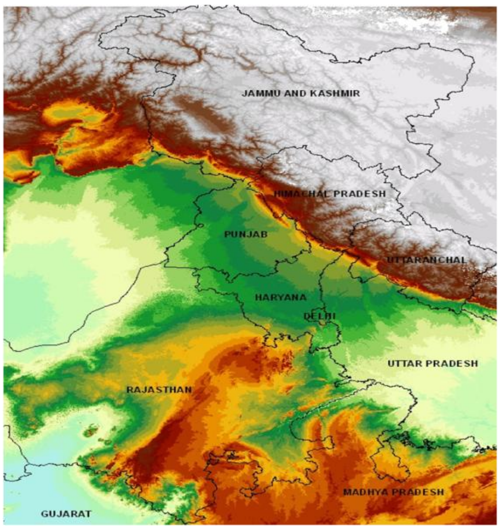


(a) DEM (Default) (b) DEM (Modified)

Fig.5.3-The complexity of the terrain captured at models' resolution



(a) DEM (Default)



(b) DEM (Modified)

Fig.5.4-Difference in the datasets of Digital Elevation model

5.1.3. Leaf Area Index

The model uses in default a look up table approach in which each USGS landuse-landcover category assigned a constant leaf area index over the models' simulation. But that is not true since leaf area index varies with time for land use categories which are well explained by Fig 5.5. The temporal profile for every vegetation functional type for the particular season is graphed. It shows the variability and dynamicity. This would modify the continuous feedback mechanism in the land surface model. Proper representation thus is expected to improve the skill of the model.

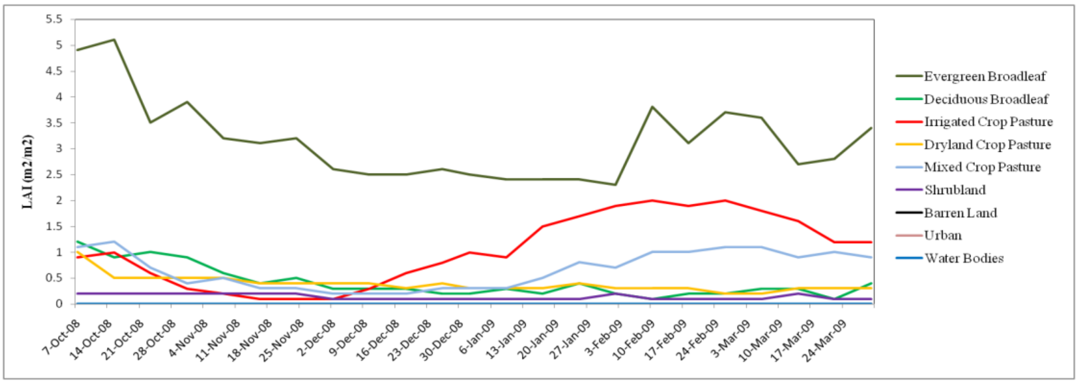
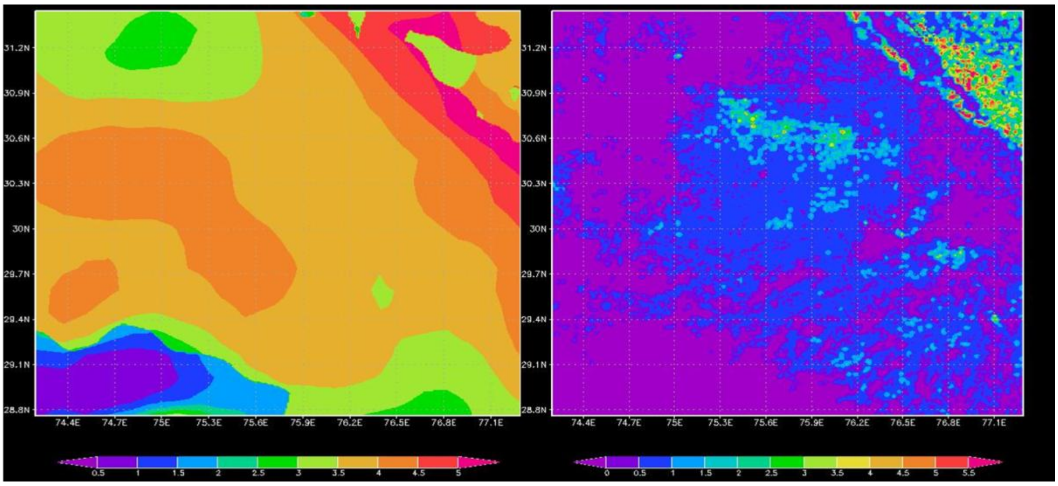


Fig.5.5-Temporal profile of leaf area index for different vegetation functional type

Fig 5.6 is a representation of October month leaf area index. It demonstrates that the new LAI information from MODIS can better capture the dynamic variation in the study area. On the contrary, the LAI based on LUT approach yield unrealistic values. For example, the generated LAI value of 5 for deciduous forest in winter season is much beyond reality. Moreover, in reality as shown in modified data set, the LAI for plains of Punjab during October is very low because a lot of the area comprised of bare fields but default values as presented in look-up table approach shows LAI values in range of 3.5 to 4.



(a) LAI (Default) (b) MODIS LAI

Fig.5.6-The difference in LAI between the sources

5.2.Impact of land surface boundary on weather forecast output

The Statistical parameters RMSE, MAE and MAPE are used to measure the bias of the output with the actual station data while the improvement factor quantifies the impact of updating the datasets on the models' performance. The formula for the calculation of the measures and the significance of each is mentioned in the Appendix.

Modified Run (EXP) showed good results for temperature at 2m as modified datasets could capture the land fluxes in a detailed manner with more refined inputs for albedo, roughness length and evapo-transpiration. It helps in capturing the energy exchanges at mesoscale level. The improvement factor of modified run over control run is 21% with a mean RMSE of about 1.37 °C within the simulation period. The differenced image (EXP-CNT) has a magnitude from -4 °C to 6 °C with maximum area under -2 °C to +1 °C. The highest magnitude of +ve difference are found in high elevation and the highest magnitude of –ve difference (i.e. the temperature is predicted low than in default run) are found in plain immediately next to the hilly terrain. The models' output is known for cold bias for maximum temperature and warm bias for minimum temperature. This is reduced with the modified run by representing the differential heating in the surface thus, altering the energy fluxes contributing to the rise and lowering of temperature. The warm bias in the minimum temperature is reduced by representing realistic surface sinks of heat absorption and emission, while the cold bias of temperature is reduced by proper measure of incoming radiation as an effect of the terrain representation. Also, it is clear that modification in the representation of initial conditions has improved the temperature inversion due to orographic effects. In Haryana where almost 85 % of land has been upgraded to irrigated crop pasture, in the month of October there is a difference of about -2°C for the night temperatures and +1°C for the morning temperature

As for surface pressure, most of the study area is in plain where abrupt changes in height is not eminent, the pressure slight difference between the control run and modified run. But in hilly region where height gradient is high there is quantifiable change in pressure. Since pressure is more influenced by the density of air and thus by altitude. Since the validation stations are in plain only a less improvement factor is recorded accounting to 4 %. The mean RMSE is 5.0485 mb. Similar effects of landuse and orography are also noticed in pressure output like that of temperature.

Relative Humidity estimates at 2m shows a very good improvement factor of 29.81 %. It is mathematically calculated as a function of temperature and pressure. Especially in areas where the land cover has changed like in areas of Punjab& Haryana and refined terrain representations in hilly parts of Uttrakhand the improvement is considerably high. The average RMSE of 10.807 % is observed with the modified run. The differenced magnitude ranges from -12% to +12 % with maximum values in ranges -6% to 9%. The highest -ve is in plains and the +ve magnitude is in elevated areas. This accounted by the near to real representation in terms of terrain and surface land cover with vertical component of leaf area index.

Wind movement is affected by pressure gradient, roughness factor, etc. It is very clear from the comparison that either control or modified run are not able to capture wind movements in an accurate way for the simulation period with a average RMSE of 1.65 m/s. An improvement factor of 12.66% is noticed. This might be accounted from the model's inefficiency in predicting the wind speed. Considerable number of studies has also accepted the models' over predicting behaviour for wind speed due to lack of parameterization available for resolving roughness elements. Anyways this over prediction is to some extent handled by the modification. Improvement factor is high in areas where the irrigated crop pasture alteration has occurred. The months of October the areas in dryland crop pasture show an increased wind speed while in irrigated crop pasture conditions presence of crop acts as a barrier to the wind flow. But this barrier is not that efficient since the month of October is the start of the season and plants get well established only in the months of January and February. Might be the simulation in that period would have reduced the RMSE to a good extent and enhanced the improvement factor.

The difference in rainfall lies in between -100 to +100 mm for modified and control run on a cloud burst day with maximum magnitude in range +20mm to -20mm. The source point of the cloud burst is significantly revealed in modified run. Rainfall is a resultant of combined processes of physics and dynamics of a certain location. Representing the physics of a particular location here has captured the development of the processes in a more realistic way. The amount of rainfall predicted by the EXP run is also near to real conditions though little over prediction occurs at some places. A magnitude of + 10 to 20mm is found distributed in the plains when compared to the CNT run, in places where the up gradation of the class from dryland to irrigated crop pasture has taken place. The hills show a realistic rainfall pattern with an increased rainfall amount due to the actual representation of orography and surface land cover in terms of leaf area index, especially in areas with evergreen forest cover.

Solar radiation also showed high difference over the control run from -50 W/m2 (for plains) to +500 W/m2 (for complex terrains). The improvement in the solar radiation improved with the finer terrain representation since the radiation on the earth surface is variably received by the surface at a particular location based on its orography.

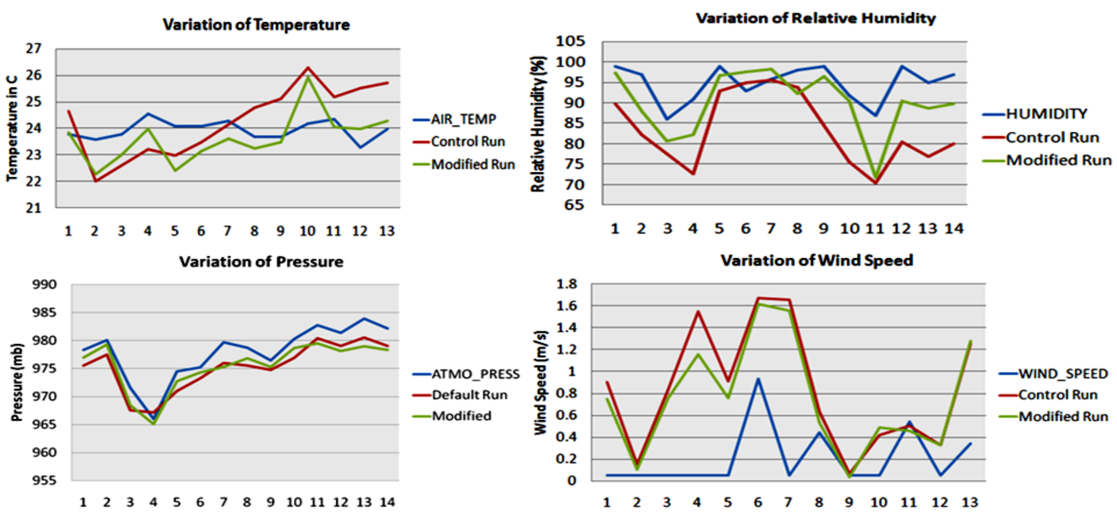


Fig.5.7-Graphs showing the comparison between the simulations and the actual station data (blue) across stations for a 12-hr simulation from 1.10.2008 12:00 GMT to 1.10.2008 23:00 GMT

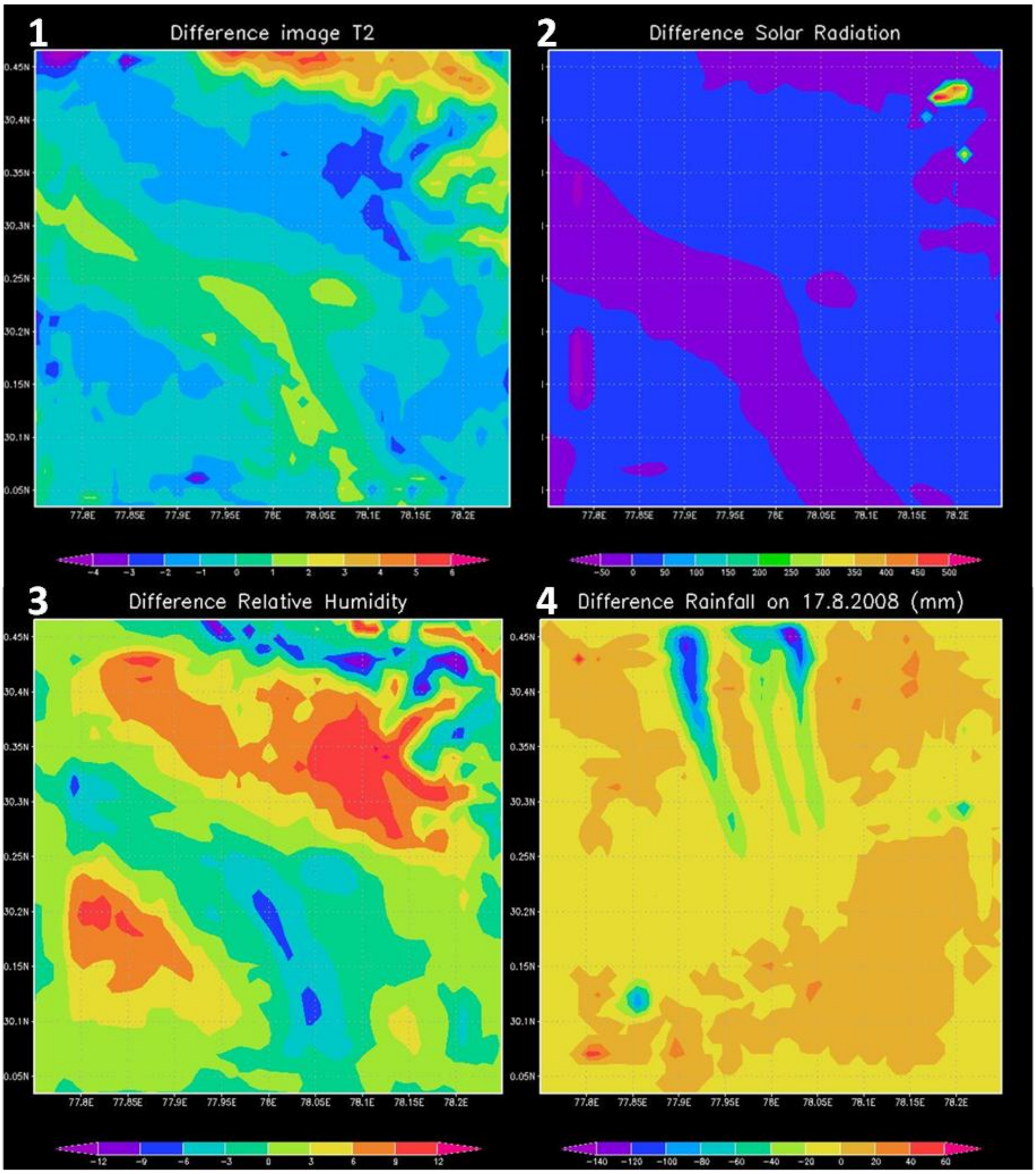


Fig.5.8-Differenced images showing the difference between EXT and CNT. (1) Differenced image of temperature at 2m, (2) Differenced image of solar radiation, (3) Differenced image of relative humidity and (4) Differenced image of rainfall

5.3.Evaluating the weather simulation at different lead times

Having investigated the impact of the modification in the initial state of land surface parameters, the next critical step would be the evaluation of the model's skill to forecast weather at various lead times. As mentioned earlier the forecast is done for 7 days, 15 days, 30 days and 45 days. Same statistical measures like RMSE, MAE and MAPE are used to evaluate the model's skill in forecasting for seven weather variables like Maximum Temperature, Minimum Temperature, Solar radiation, Pressure, Precipitation, Relative Humidity and Wind speed. Agreement Index is also calculated to understand the degree of agreement the forecast has with actual data.

Forecast behaviour for 7 days is explained here. The daily maximum temperature has a root mean squared error of 1.58 ° C with a mean absolute deviation of about 0.583°C and with an agreement index of 0.69. The observation is that it under predicts the extremely high maximum temperature. The mean percent deviation is about 8 %. The root mean squared error for daily minimum temperature over the 7 days is about 1.57 ° C. The model over predicts the minimum temperature to an average of 0.87°C. The minimum temperatures for almost all stations and days are satisfactory with an average percent deviation of 12% and agree with an index of 0.75. For average daily temperature the RMSE is about 2.71° C with an absolute mean deviation of 1.52 ° C. The solar radiation is over predicted by the model amid a RMSE of 3.19 MJm^{-2} and average absolute deviation of 2.94 MJm^{-2}. Percent error deviation is 8% with an agreement of 0.63. Precipitation is also over predicted. RMSE is 0.12 mm, average deviation of 0.07 mm and an agreement of about 44%. The surface pressure has an RMSE of about 122.18 mb at about 10% percent deviation from the observations. There by and large over prediction of the surface pressure of mean deviation of 102.28 mb. The agreement index is very low of about 0.095. The relative humidity is forecasted at an RMSE of about 19.00343% with a mean absolute deviation of 16.44 %. As a whole, under prediction of relative humidity is observed with a mean percent error of about 21%. The actual relative humidity agrees with the forecasted relative humidity at an index of 0.52. Wind speed forecast is not convincing. The RMSE is in range of 2.39 ms^{-1} with mean absolute deviation of 2.03 ms^{-1}. It is mostly over predicted with an agreement index of 0.22.

Similar pattern is observed with the model prediction throughout the forecast at different lead times of 15 days, 30 days and 45 days. The results are tabulated in Table 5.1

Table 5.1 Error Statistics and Behaviour of the forecasts at different lead times

Forecast Lead Time	Weather Variables	RMSE	MAE	MAPE	Index of Agreement	Behaviour with Actual data
15 days	Max Temp*	2.81 ° C	1.895 °C	10%	0.51	Under-Prediction
	Min Temp*	2.72 ° C	1.07 °C	16%	0.68	Over-Prediction
	Solar Radiation	4.04 MJm^{-2}	3.54 MJm^{-2}	19%	0.35	Over-Prediction
	Precipitation	0.26 mm	0.17 mm	126%	0.48	Over-Prediction
	Pressure	110.31 mb	95.09 mb	11%	0.11	Both with large bias due to **over prediction**
	Relative Humidity	15.9 %	12.74%	18%	0.52	Under-Prediction
	Wind Speed*	2.37 ms^{-1}	2 ms^{-1}	819%	0.18	Over-Prediction
30 days	Max Temp*	3.3 ° C	3. 75 °C	13%	0.6	Under-Prediction
	Min Temp*	3.05 ° C	2.46 °C	19%	0.59	Over-Prediction
	Solar Radiation	4.03 MJm^{-2}	3.66 MJm^{-2}	17%	0.49	Over-Prediction
	Precipitation	0.53 mm	0.16 mm	246%	0.11	Over-Prediction
	Pressure	183.95 mb	149.59 mb	15%	0.11	Both with **huge under-prediction**

30 days	Relative Humidity	14.66 %	11.52 %	19%	0.63	Under-Prediction
	Wind Speed*	2.3 ms^{-1}	2.02 ms^{-1}	857%	0.19	Over-Prediction
45 days	Max Temp*	5.05° C	4. 34 °C	18%	0.48	Under-Prediction
	Min Temp*	4.13 ° C	3.07 °C	22%	0.5	Over-Prediction
	Solar Radiation	4.07 MJm^{-2}	3.69 MJm^{-2}	18%	0.597	Over-Prediction
	Precipitation	0.43 mm	0.12 mm	298%	0.13	Over-Prediction
	Pressure	232.17 mb	175.43 mb	18%	0.02	Both with **huge under-prediction**
	Relative Humidity	19.66 %	16.24 %	28%	0.51	Under-Prediction
	Wind Speed*	2.37 ms^{-1}	2.11 ms^{-1}	857%	0.2	Over-Prediction

Note: * denotes that the statistics are calculated with Actual Station data that has unrealistic values for those variables which is explained later in this section. Statistics of 7 days is discussed in earlier paragraph.

5.4.Analysis of the pattern in predicting weather parameters:

5.4.1. Surface Temperature at 2m

On an average for daily mean temperature the model forecast over predicts the parameter on a range 2.5 ° C to 5 ° C. However, for maximum temperature, when an extreme high value occur the model under predicts the value, while for medium and low values of maximum temperature the bias is low. This highlights the cold bias in the warmest temperature forecasted i.e. under prediction of the highest temperature values. An overall warm bias in the minimum temperature forecast is also noticeable. The model is able to record medium to high minimum temperatures but extremely low temperatures are little over predicted. This bias increased slowly over the lead times and also observed in plains. This phenomenon of cold bias of warmest temperature and warm bias of the coldest temperature (as observed in Fig 5.9) is not a new phenomenon. It is one of the well-known model errors that had been shown by earlier studies. The cold bias is a phenomenon that might be occurring due to problems in Planetary Boundary Layer (PBL) parameterization schemes just because it allows full PBL mixing, thus causing an under estimation of turbulent mixing. *(Welsh et al., 2003; Das et al., 2008; Hanna et al., 2010; Flaounas et al., 2010; Manju Mohan and Shweta Bhati, 2011)*. Another angle of investigate is done, since the vegetation parameters are well represented in the models run, one would naturally expect a well modelled flux variations and improvement in the models' forecast skill. The transpiration component is taken care of by this methodology while the evaporation component is not considered. One cause for this as judged by researches so far is the over estimate of the bare-soil evaporation thus increasing the evaporation from the bare soil physics formulation. Thus, as vegetation representation is increased, more of the surface fluxes are determined by the canopy physics and less are determined by the bare soil physics. Another possible explanation is that the net radiation at the surface increases as vegetation increases, owing to a decrease in albedo over vegetation as compared with some light-colored bare soils, leading to larger sensible heat flux over more vegetated surfaces leading to cold bias. (*Yang et al., 1994; Yucel et al., 1998; Mitchell et al., 2002; Kurkowski et al., 2002)*.Warm bias for minimum temperatures is also visible in the forecasts but they are not of high magnitude.

The over prediction occurs most in Ludhiana station (7.59 °C) where the diurnal range is very high for 4 days of the simulation. But this seems to be unrealistic (minimum temperature) since the simulation month is March and April, and the diurnal variation in this month over the particular location is not high. Also when verified with online archives at the station location and global summary of a day real time data collection system of NOAA it is not showing high diurnal variation for those days. Even the nearby station location doesn't show this high diurnal range for the same dates. The maximum temperature of the observed locations agrees with each other, while high deviation is found in the minimum temperature. Fig 5.9 demonstrates this deviation of the actual station data. Thus this is probably due to some system error while measuring the actual data. (Refer Fig. 5.10) The minimum temperature when validated with the observed global dataset for few locations gave a very good agreement with a RMSE of range 1.5 to 3.9 ° C for 7 day to 45 day respectively.

Except for that station and particular dates, the maximum and minimum temperature shows very good agreement with that of the actual weather. The bias that is mentioned above exists anyways with high cold bias prevailing in the maximum temperature data as the forecast period moves from short to long range forecast where the minimum temperature are normal while maximum temperature goes to extremities in Indian conditions. Cold bias are prominent is stations with high elevations than at plains. While at valley and plains the warm bias exists, but in low quantum.

5.4.2. Solar Radiation

The overall behaviour of the models' forecast for solar radiation variable is over prediction, when compared to actual data. Starting with a RMSE of 3 MJm^{-2}, the error propagation of the prediction is very slow, expect for days with extremely high solar radiation. Underestimation of cloud fraction can be accounted for high solar radiation over maximum days. The over estimation of the same can be reason for low solar radiation than actual are also observed *(PaiMazumder, 2012)*. These days when noticed are the days where false prediction of rainfall has taken place. That is the cloud fraction has become high thus leading to a low solar radiation which is not a reality. Lack of parameterization for the land cover would have also led to the bias in solar radiation; since albedo for each landuse landcover is different. The coarser gird resolution of 10km might have led to the homogeneous representation of landuse landcover for the 100 km2 area. Thus variation is lost especially in the Shivalik mountains where the forest is not continuous. The high bias in solar radiation occurs at the stations in the Shivalik hill chains. Certain studies show that the bias in the prediction of the solar radiation is associated with the way the radiation is calculated in the model. It accounts for the direct radiation from the sun in the vertical column while the scattered radiation from the horizontal directions also accounts to the total radiation. The density of the air above the surface also has an effect on the solar radiation that reaches the ground. The density of the air is decided by water content and the aerosols along with dust particles. The presence of aerosol layer in the Planetary Boundary Layer is not considered by WRF model which might also lead to under or over estimation of the solar radiation *(Welsh et al., 2003)*.

There is one more behaviour that is observed, that when solar radiation is over predicted the under prediction of relative humidity occurs, while with the under prediction of solar radiation, the relative humidity is over predicted. When enquiring this event, it is because relative humidity is a function of temperature and pressure; during cold bias of surface temperature the over prediction of relative humidity occurs and during warm bias the under prediction of relative humidity occurs. (Fig 5.11) As solar radiation is the prime source of energy with which the energy fluxes and processes gets ignited, it may also be told that the solar radiation received at the surface is low due to unrealistically high density of air (pressure) or over prediction of cloud fraction *(Welsh et al., 2003)* in the atmosphere; the temperature that is forecasted also becomes low. While warm bias in coldest temperature might be due to over prediction of solar radiation that is absorbed by the surface and so the cooling down doesn't take place at a rate that is true in ground. The over prediction (warm bias) trend is more observed in plains while the under prediction phenomenon (cold bias) of solar radiation occurs mostly in stations of high elevation.

5.4.3. Precipitation

For a station in upland plains, out of 8 precipitation events in the simulation period the models' forecast is able capture 6 precipitation events. Of the 6 precipitation events an average deviation of 0.7 mm in the amount of rainfall recorded. It has predicted false event 3 times with a quantum varying about 0.15 mm or lower. Especially these false alarm starts after the 7^{th} day and the frequency increases after 20 days of the models' simulation start date. The false alarm ratio has increased with increase in elevation. This might be because of the models cumulus parameterization schemes. Another reason might be error propagation through the days, since these false alarms occur with long run. But still the forecast is quite dependable as the magnitude of the false alarms is very low.

The pressure predicted shows nearly 18% variation which might have induced rainfall and thus be a part in simulation of false alarms. Also one interesting pattern is observed in the prediction of pressure; the deviations in the early lead times are because of lesser over prediction and while in the long forecasts the deviations are due to under estimating of pressure which is very high in magnitude. The actual pressure is almost constant over the forecast period. For the initial runs, the actual pressure is well agreed by the forecasted pressure but as forecast time increases the ability to be in conformity with the actual estimate decreases. Thus we can say the error propagation across lead times is present which is very significant with the pressure estimate. This pressure underestimation might have led to the false alarms in the precipitation at later stages of the forecast.

As it is well known there is a strong relation between occurrences of precipitation with solar radiation. When there is a precipitation event, the solar radiation is low due to cloud cover. During this false prediction the error in forecasted solar radiation is high.

5.4.4. Wind Speed at 10m

Wind speed when validated gave poor agreement with the actual data. But like that in the case of minimum temperature, the wind speed data from the ground station is not trustworthy. When validated at points from the global summary of a day data it gave a very less RMSE of 0.8 ms^{-1} to 1.5 ms^{-1}, with a very surprising pattern of decreased deviation over the increase in lead time. Anyways to some extent over estimation of wind speed is there in range of 1.5 ms^{-1}. Especially these biases are mostly prominent with moderate and low elevation. The bias may be accounted from the model's inefficiency to resolve sub-grid scale roughness at a coarser resolution of about 10 km. This is primarily due to the absence of parameterization for land surface processes in the model in which terrain is also accounted. Also the artificial emergence of low pressure belts that develop due to the reasons mentioned above influences the movement of wind at little higher speeds to these belts than actual. While this phenomenon decreases as we move up in the vertical profile, since WRF mode is a terrain following model, where lower boundaries are more vulnerable to the representation of the terrain structure. *(Jorba et al., 2008; Katsafados et al., 2011; Jiménez and Dudhia, 2012)*

5.4.5. Relative Humidity

Relative humidity is calculated as a function of water vapour mixing ratio, temperature and pressure. High deviation is observed for the station located in the upland plain. This might be accounted to problem in smoothening of terrain near the little high elevation due to coarser resolution of the model (10km). Relative humidity is largely under predicted to a magnitude for plains and upland hills while over predicted for mountains with deviation ranging between 11% and 16%. Over prediction also occurs for extremely low values of relative humidity.

The stations which show cold bias in temperature has a behaviour, when the temperature is same as actual then relative humidity is also same as observed relative humidity but when the cold bias starts then the relative humidity is over predicted by the model. This phenomenon is increasing with increasing lead times (not because of error propagation but because of the shift of weather forecast period from normal weather (March) to summer season (April)) and also with increasing elevation of stations. The stations at plain show a little under prediction due to warm bias of temperature while the stations in above medium show over prediction due to the cold bias in temperature. This is obvious because the error in the prediction of temperature, especially the cold bias in the warmest temperature and the warm bias in the coldest temperature has propagated in higher level in forecasting relative humidity. There is an interesting phenomenon observed for some stations with low elevation. The 45 day forecast gave a very good RMSE and agreement index than the 7 day forecast. This is because the 7 days of simulation had high relative humidity in reality, while the model due to bias in predicting extremities forecasts values with huge deviation. While in the 45 day forecast the simulation days involve medium relative humidity and the model forecasts match with the actual data thus reducing the error. This explains that models can give very good results at normal conditions and seasons. But when extremities occur they are not able to capture it.

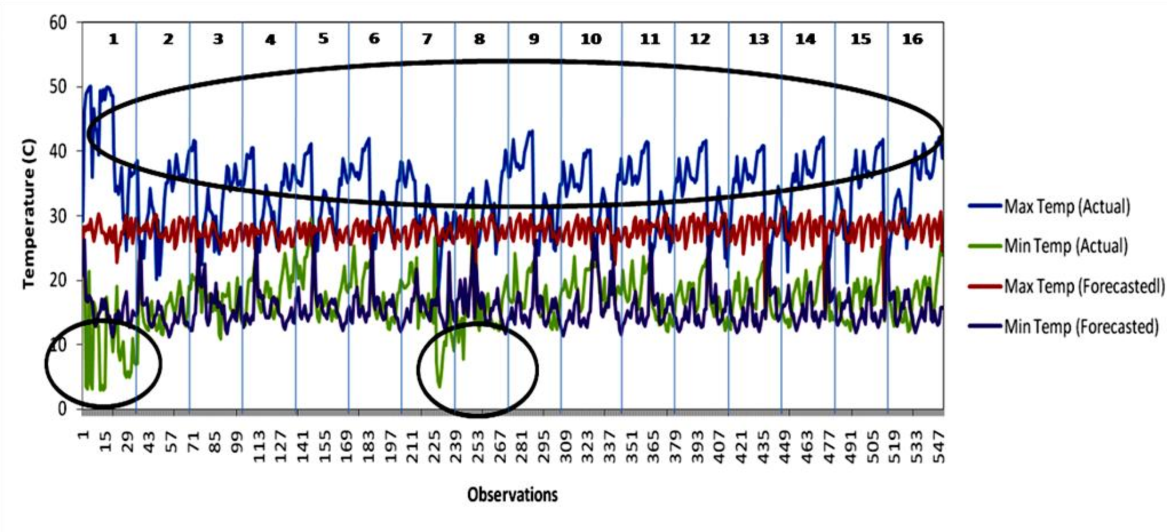


Fig. 5.9-The graph showing the biases existing in the Temperature forecast.

The oval in the up shows the cold bias in maximum temperature that increases with increase in time and more prominent in high elevations. The circles down show the warm bias in minimum temperature which is prominent at plains. The numbers marked above in the figure denotes stations for which the comparison is made. *(Refer to Appendix for the station details)*

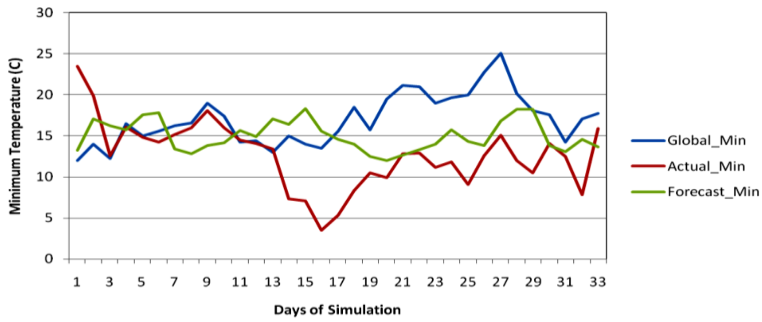


Fig. 5.10-The graph showing the high erroneous data for certain days in recording the minimum temperature at a particular station.

Here Global_Min represents the observed minimum temperature data obtained from NOAA for the particular location.

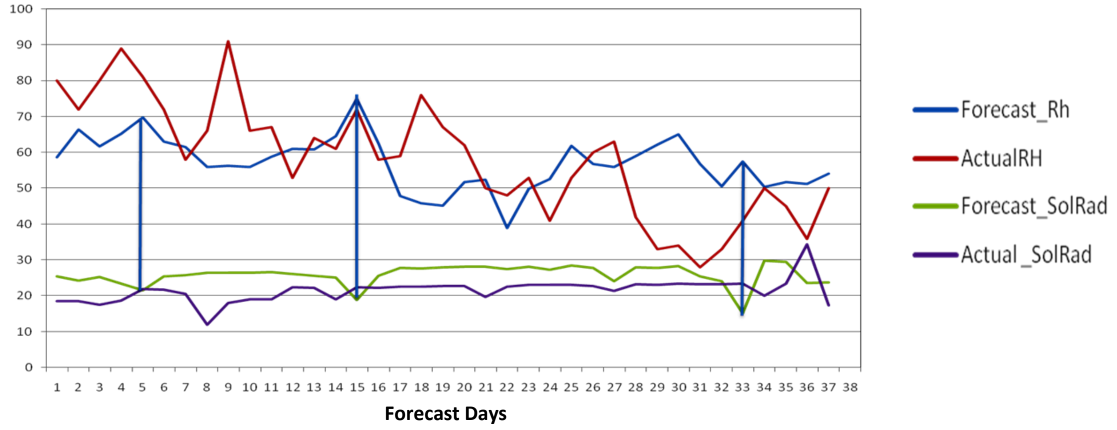


Fig. 5.11-The graph showing the relation between relative humidity bias and bias in predicting solar radiation. The blue vertical lines depict the exact values where this phenomenon is sharply observed.

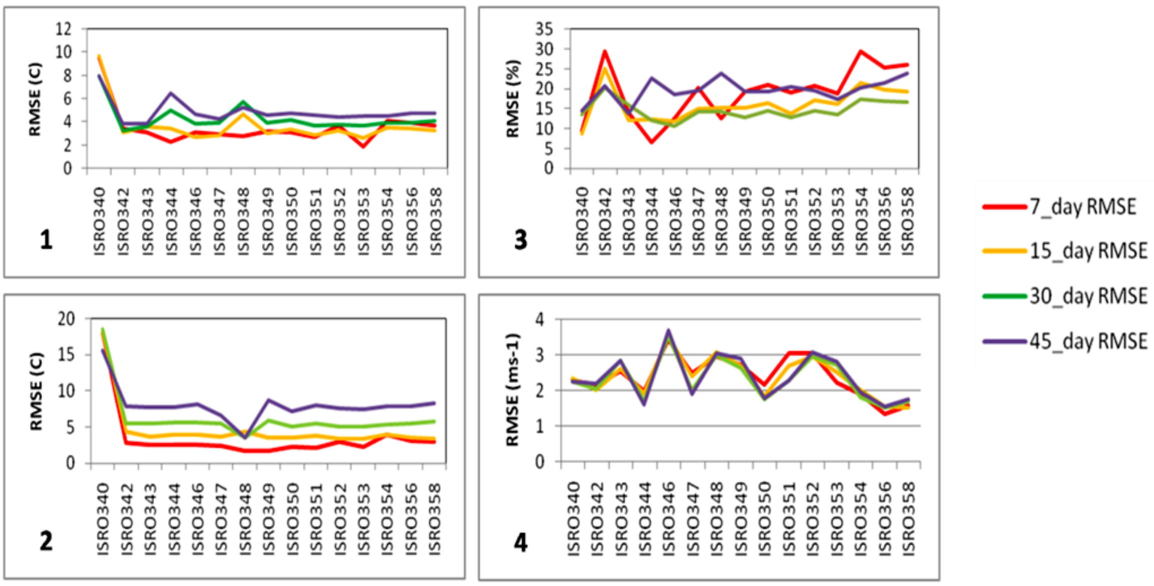


Fig.5.12-Evolution of the root mean squared error over lead times for 15 stations. (1) Minimum Temperature (C), (2) Maximum Temperature (C), (3) Relative Humidity (%), (4) Wind Speed (ms^{-1})

5.5.Investigating the fidelity of NCEP-CFSR

NCEP-CFSR is the 3rd version reanalysis specially modelled with high spatial and temporal resolution across the globe at 50km (approx) resolution. Some errors are inherent in the dataset itself from modelling errors and the user induced error due to interpolation at 10km to match the WRF output. Thus validating with the actual data will show the integrity of the data. The dataset is also compared with forecasted data from WRF to evaluate the forecast skills of each of the data.

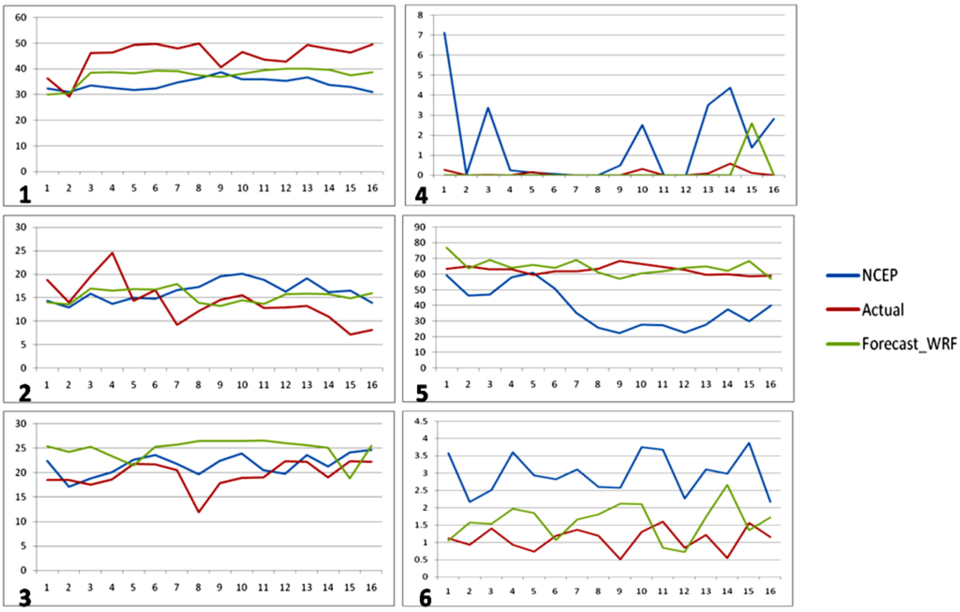


Fig.5.13-Comparison of the weather variables between various sources across stations (1) Minimum Temperature (C) , (2) Maximum Temperature (C), (3) Solar Radiation (MJm^{-2}), (4) Precipitation (mm), (5) Relative Humidity (%), (6) Wind Speed (ms^{-1})

It is clearly seen from the above graph that the WRF gives better scenario of each variable with a good agreement to the actual data. An average improvement factor of 30 % is measured with lowest improvement factor in variables like solar radiation (8%) and minimum temperature (18%). Although these improvement factors decreases very slowly with time, in our case until 45 days the improvement factor remains positive for all weather parameters.

5.6.Verifying the ancillary inputs

The area under wheat is calculated from the Enhanced Vegetation Index as mentioned in the methodology. The output from the method is found appreciable. The aggregated to each districts and is validated district wise from the reports published by government. It gave a very good agreement of 0.965 with an average deviation of area district-wise by 4.99%. To account for the calculation of sowing date, the EVI image is used to calculate as mentioned in the methodology. Four major sowing dates are obtained of which majority of wheat area lies in Nov 6, 2008. This is found to be optimal for the crop model also found after calibrating the model. This sowing date thus obtained agreed in large with the monthly reports published at state level and some earlier researches done at Punjab and Haryana.

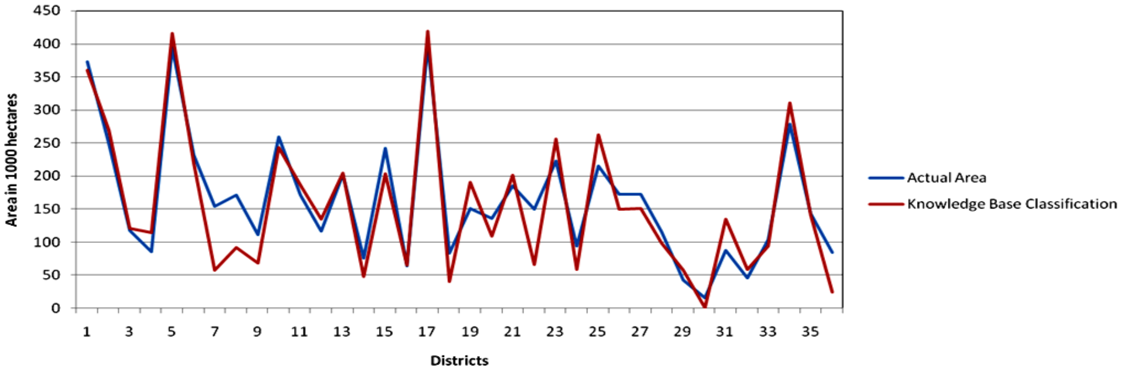


Fig.5.14-Contrasting between the actual district-wise area and the knowledge based classified wheat area

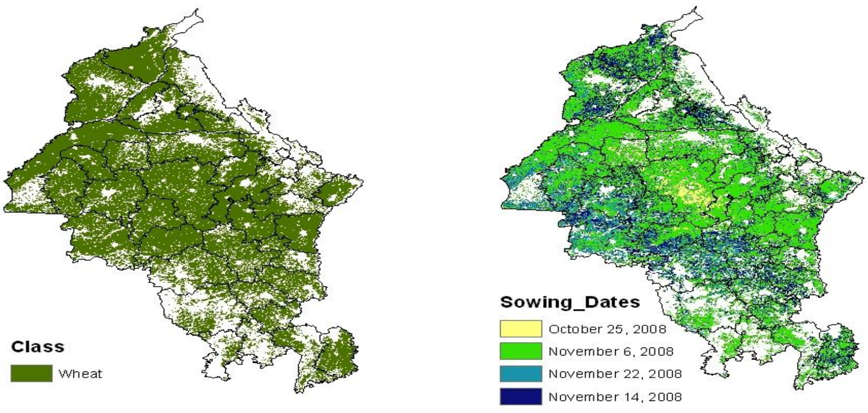


Fig.5.15-(a) Left map shows the wheat classified map (b) Right map shows the spatial map for sowing dates

5.7.Sensitivity Analysis

Crop model appears to be a black box, where some inputs are given and some outputs are obtained. But what is the process behind the models' simulations, which parameters affects the models' performance to a greater extent, etc., are some of the aspects to be known to efficiently utilize the model for required purpose. Thus, the sensitivity analysis of the model is done to understand the critical parameters that affect the crop yield. Each parameter is varied manually and its impact in terms of crop yield/ nitrogen content etc, can be computed, this way quantifying that parameter's importance to the final output. The model is tested for its sensitivity to crop management parameters, genetic parameters and for methods (equations) to predict various processes in the models. The discussion will first consider the genetic parameters. The parameters that are specific to a cultivar found in the ecotype files are found to be very sensitive to the model. The number of days required for vernalization (P1V) is found to be significant to the models' performance. Here when it is increased 5 days, the yield is predicted high to a 6-10%. But the days required by the crop also increased above the normal cultivar duration. When this parameter is reduced by 5 days, then the same magnitude under estimation of the yield is observed with reduced MDAY (day of maturity) than the actual. Same pattern is noticed when altering the percentage critical photoperiod when reduced to 5 % gave yield with a magnitude of 25% reduction and short crop duration. Increasing gave unrealistic maturity dates with high yield of upto 15-20% rise. For some station the model gave error of convergence since the % of photoperiod takes long duration due to low solar radiation at the stations and the duration of the crop even exceeded the days loaded in the weather database. The kernel size coefficient (G2) greatly decreased the yield when reduced. Since wheat kernel account to its final harvest the maximum size of the kernel is determine by this parameters. Thus the reduction affected the yield. Other parameters are also significant to the model but in a magnitude that is lower to the above mentioned parameters. One component in the Species file which is specific for each species of wheat used is found to be very influencing for the yield estimation. It is the PAR conversion to dm ratio, before the last leaf stage (PARUV). This ratio tells the model the efficiency of the species to convert each unit of the photosynthetically active radiation (PAR) to effective dry matter. A check should be kept at this parameter since the increase of the parameter would give high yields with normal duration which may not be true in reality in field with the same species. Thus the models bias increases leaving the user confused about the cause for the bias. Reducing the PARUV clearly reduced the yield.

Regarding the management parameters, the plant population has a high degree of sensitivity to the model, since the number of plants per unit area decides the yield. An increase in the plant population in reality gave increasing yields to some 5%, but after which there is a decline. Optimal plant population gave appreciating yields with reduction in plant population gives reduced yields again. The plant spacing also had an impact with optimal spacing giving good results; the yield got decreased even with both increase and decrease below that plant spacing. The sowing depth also affected the model's output greatly since in dwarf wheat varieties, an increase in the sowing depth increases the days of emergence , now that the plant has emerged it need optimal vernalization and photoperiod to develop, but as the emergence phase is delayed the winter weather that is suitable for the crop might be in progress. The crop starts developing lately with lessened reserves weight and thus a lessened yield. Even reduced of 2 cm of sowing depth affected the yield by 5-12% reduction. One more important parameter is the sowing date, which affected the models performance greatly, the model is not able to converge with increased sowing date since the temperature optimal for vernalization and photoperiod is never attained. On another case a decrease in sowing date even by one week than optimal condition increased the yield by 7% but with large duration of the crop to complete its life cycle. A little increase in the sowing date decreased the yield by 11% with less duration to attain maturity. Other management parameters like soil characteristics, number of irrigation schedules, irrigation dates, fertilizer application dates, and amount applied also plays significant role in the model's performance. The sensitivity of the model to the weather parameters is the main focus of the project which is discussed in the next section.

5.8.Yield Forecasts

5.8.1. Station-based Forecasts

Station/Point based forecasts were generated with the station weather data and WRF ensemble for different time scales. A CNT_YD estimate is also generated for a reference as the yield simulated from the real-time observed data is assumed to represent the actual conditions. The forecasts show that the deviation from the reference increases with increase in the lead time. That is as the real-time weather data is getting replaced by the WRF weather forecast the forecasted yield starts deviating from the reference yield. But a strange behaviour in ensemble forecasts of station and 15 days, station and 45 days are observed when compared with actual yield. The reason for the behaviour is explained later in the chapter during validation.

5.8.2. Regional Forecasts

At present times most of the focus is towards forecasting the crop yield at regional level to foresee the opportunities and risks at a synoptic scale and respond in a totality. After the calibration and sensitivity analysis the forecasts are generated at a resolution of 10km at different time scales from 7 days prior to crop forecast till 45 days prior to the forecast. The outputs of the crop model includes daily summaries of leaf area index, reserves weight, grain weight, PAR use efficiency and seasonal summary of anthesis date, maturity date, harvest date, dry weight, yield and yield components, water, nitrogen, organic carbon and phosphorus usage for each grid point. The spatial yield varies well spatial across the forecasts. The NCEP estimates gave values mostly in range of 3000 to 3800 kg/ha. The deviation from this value in both direction starts with increase in the lead times. Especially the higher deviation in positive direction, i.e. higher values of yield is observed with increase in lead times. The deviation occurs at most in upland plains and hills. The reason behind the deviation and the spatial variation is stated in the validation section.

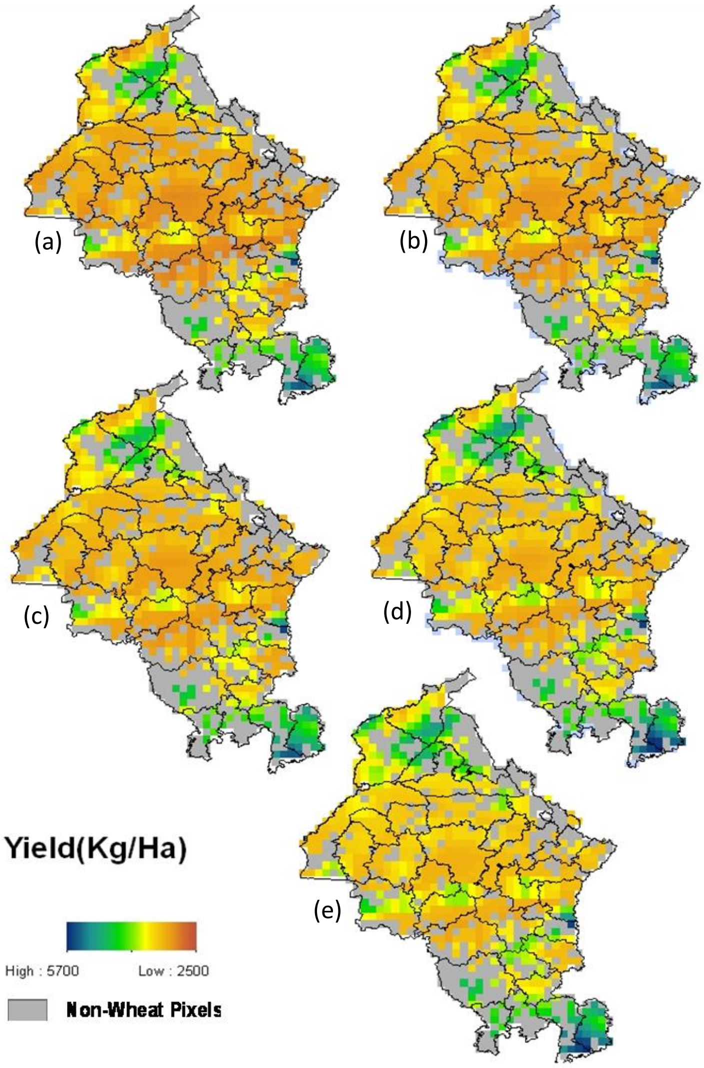


Fig.5.16-Yield forecast at regional level at various time scales (a) Full NCEP estimate (b) NCEP + 7 days advanced ensemble forecast, (c) NCEP + 15 days advanced ensemble forecast, (d) NCEP + 30 days advanced ensemble forecast, (e) NCEP + 45 days advanced ensemble forecast.

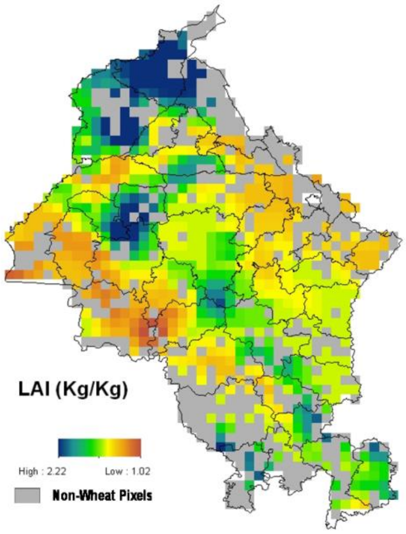


Fig.5.17-LAI (maximum) at regional level simulated by 45 days forecast

5.9.Validating the Crop Yield

The main objective of the study is to assess the degree of transferability of the extended weather forecasts to extended and meaningful crop forecasts benefitting the stack holders at regional level. Two strategies had been followed to evaluate and compare between the models' performance as explained below.

5.9.1. Point based Analysis

A station is assumed as a representative of the district it belongs to, so as to validate with district level yield data. As mentioned in the methodology the full length station observed weather data is used to generate a control forecast CNT_YD. The weather forecasts for the particular point is extracted from the WRF model's output and it is used in combination with observed data in the station to generate forecasts ranging from F6 to F7 (refer to section 4.3.2.7.a). These way 12 stations across Punjab are taken for this evaluation. The main aim of this assessment is to study the behaviour of the crop model with observed data and test for the degree of predictability associated with these station points since as practise the point based yield assessment is traditional and more widely accepted strategy for study of plant behaviour to its environments.

The yield estimation by CNT_YD gave an RMSE of about 201.21 kg/ha and highly correlated with actual yield at r^2 of 0.965. With this as reference, the other composite forecasts are compared. The F6 *(Actual station+7day)* forecast with 7 day forecast had a very less impact on the yield forecast. The RMSE is slightly increased to 209.87 kg/ha.

The 7 day forecast (F6) is very much comparable to the actual station forecast (CNT_YD). This is because the 7 days at which the forecast is fed to the model is at the end of crop stage, i.e. at a stage where the rate of accumulation of grain weight starts decreasing. Thus the influence of weather variable at this stage is very slight, thus making no great difference from the CNT_YD. The F7 (refer to methodology to understand the forecast coding) has an average RMSE of 214.595 kg/ha. Here the forecast deviation can be more observed at high elevation areas where slight over prediction of yield occurs. This might be accounted to the over prediction in solar radiation at higher elevations that is available with the weather data. Here the effect of solar radiation is only highlighted for the reason that at this stage of crop, it is sensitive to solar radiation than any other weather variable. The bias with forecasting solar radiation probably might have propagated. Nevertheless, the 15 day forecast has made only a very little progress in the yield deviation only due to the same grounds for that of F6. F8 surprisingly simulates the yield well with an RMSE of 192.82 kg/ha which is even lesser to the CNT_YD forecast. This would be probably due to the errors that are observed in the actual data at the simulation period (discussed in section 5.4.1.1). The unrealistic minimum temperature is replaced with the forecasted data which agrees better to the real conditions. This would have perhaps reduced the error in the CNT_YD forecast, thus improving the forecast. The F9 shows a very little difference from the F8 since it has the same characteristic mentioned above. A slightly increased RMSE of 187.32 kg/ha is observed.

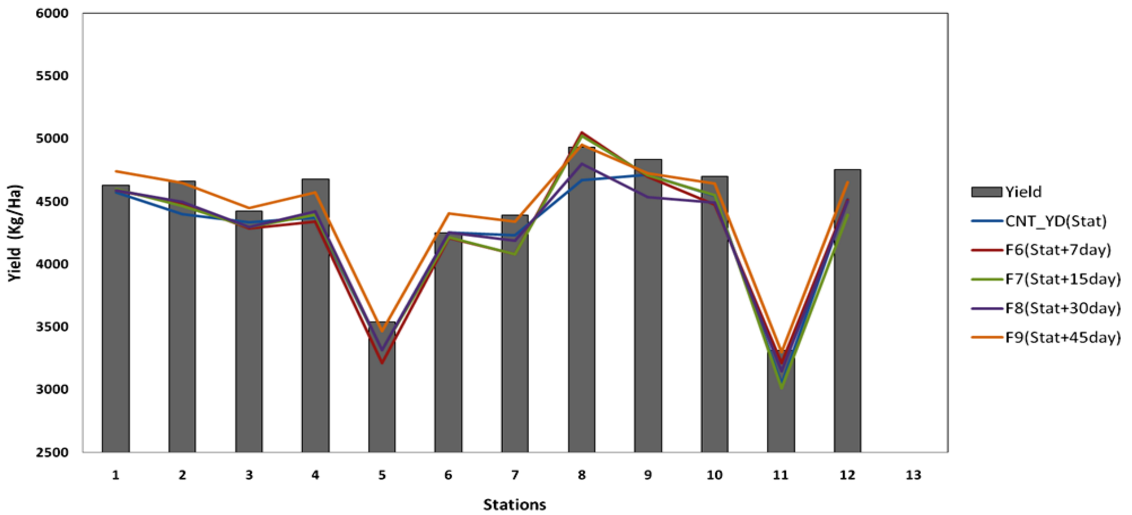


Fig.5.18-Comparing yield from different cases to district-wise actual yield

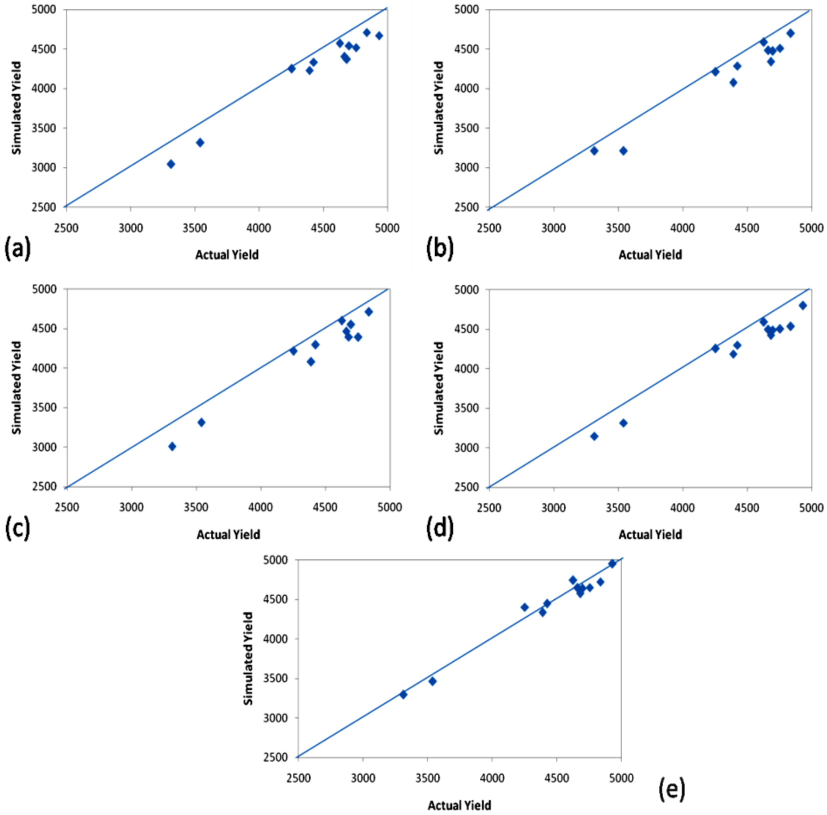


Fig.5.19-The scatter plot of different forecast cases with observed yield (station-wise) (a) CNT_YD (b) Station+7days forecast (c) Station+15 days forecast (d) Station+30 days forecast (e) Station+45 days forecast. Units- Kg/Ha

Table 5.2 Averaged Statistics for the crop forecasts (station-wise)

Forecast Case	Average Yield	RMSE	MAE	RD	MAPE	Agreement Index
CNT_YD(Stat)	4247.25	201.21	279.43	-4.13	4.13	0.96
F6(Stat+7day)	4261.92	209.87	284.89	-3.82	4.22	0.96
F7(Stat+15day)	4254.58	214.60	251.86	-4.06	4.37	0.96
F8(Stat+30day)	4253.08	192.82	221.61	-3.94	3.95	0.96
F9(Stat+45day)	4407.10	83.62	179.45	-0.42	1.59	0.99

5.9.2. Rationalizing the yield on spatial scale

The estimation with full NCEP (F1) weather data showed the least performance of all, since it is little erroneous than the WRF model's data (proved in the earlier section) due to its inherent error and the interpolation to 10km. It is basically used since it is a widely used source of weather data for spatial studies. The error magnitude ranges largely between 2 to 20 %. It mostly under predicted and sometime over predicted. Statistical measures like RMSE, Relative Deviation and Hit score between ranges 95 % to 105% of actual yield, i.e. allowing a 5% deviation either side. The hit scores are 7.32%, 39.02%, 58.54%, 78.05%, and 92.68% for NCEP, 7days, 15days, and 30days and 45 days forecasts respectively. The 45 days forecast gives a very good hit score as very well as reduced relative deviation. This can be attributed to the improvement of weather parameters in WRF forecast than in NCEP forecast. Theoretically with the use of one single dataset, or a dependable dataset, the error increases with lead time. But here since NCEP is used as an ensemble to represent first quarter along with the WRF forecast these inverse results have appeared. Predictability using this methodology on spatial basis would be discussed as a function of two factors:

Crop Characteristics

Vernalization process is very critical to wheat crops' yield as per the wheat phenology is concerned and it becomes saturated even at early stages of the crop. The crop is also highly sensitive to the critical photoperiod which also ends in the initial stages of the crop. These two processes highly determine the yield of the crop. Though these stages end up at early times, daily accumulation and optimum minimum and maximum temperatures regulates the plants growth and fractionally influences the yield. Thus the impact of weather variables as per wheat crop is concerned decreases with time. That is the weather variables influence considerably reduces as the crop moves from reproductive to maturity stage. Here the mention is it considerably decreases, not to be taken as not to have an impact at all. As per one of the studies in UK by *Lawless and Semenov, 2005* the winter wheat's yield is proved to be predicted even before 48 days with a probability of 0.95. Wheat plants accumulate fructan and sucrose in their stems during vegetative growth (reserves weight), which are remobilized during grain filling. The discussion on the reserves weight and the grain weight in section 4.3.2.3 would help understand the same for the cultivar used here. The major part of the plant growth is associated with the reserves weight accumulation. This is a result of vernalization, critical photoperiod and daily accumulation from photosynthesis. But after anthesis the reserves weight starts converting to grain weight. The variety used here has an average duration of 150 to 160 days. As conferred in the section 4.3.2.3, Fig 4.3.b the anthesis is attained at around 115 to 120 days after sowing. The remaining 35 to 45 days the plant is involved in grain filling. Grain filling in wheat depends on two major sources of carbon, namely, current photosynthesis in leaves and mobilization of stored water-soluble carbohydrates (WSCs) from the stem internodes into the growing grains *(Ehdaie et al., 2006)*.

The forecasts which the project attempts fall in major at maturity phase where the utmost impact on yield by current photosynthesis rate the impact of which is also shared by mobilization of reserves weight. In the study, the 45 day forecast has got major impact for most of the grid points since it envelops some part of reproductive stage which is more critical to the crop. Thus we can conclude that the wheat gives scope for long range forecasts provided the local attributes are stable.

Local variability due to weather

The above section states the overall predictability of wheat crop. This section would try to explain the local climatology effect in the predictability of the crop. In this study, spatially the high variability is only by weather, isolating to some extent the impact of weather on crop forecasting. The exact impacts of the variation of weather are demonstrated and how the error in the weather forecasts has propagated into the crop model is explained below.

A small underestimation of temperature would lead to higher yield. This is true in districts where the cold bias of maximum temperature has occurred. The districts especially Panchkula, Rupnagar, Hoshiarpur, Ambala which are located in the elevated regions suffer from lower yield in actuality due to complex terrain and limitations to optimal conditions for the crop growth. But throughout the different forecast cases the relative deviation is more for these districts especially for Panchkula whose elevation is in range of 1000 meters. This can be accounted to the cold bias which is prominent in hilly terrain under predicting of about 5° C. This has led to little high yield simulations in the model that is prominent in all the forecast cases; With the increase in forecast lead times this cold bias also increased in the weather forecast, here also the crop yield error for these particular districts increases with increase in the lead time for the same reason.

A under estimation of 1-2°C with lowered solar radiation leads to reduction in yield. This phenomenon is more prominent in the plains where the yield is underestimated to about 12 % to 20 % on whole for the forecast cases. This can also be related to the under prediction of day temperature and solar radiation in plains (at lower magnitude) by the weather model. The under prediction occurred due to over prediction of surface winds and false precipitation alarms. This is prominently observed in plains like Moga, Muktsar and Bathinda. The error in range of 3 to 8 % occurs in maximum temperature at these places and also a little reduction of solar radiation in range of 3 to 5 % occurs. This error has propagated into the model making a deviation from the actual forecast values. The overall performance of the coupling for these districts is under estimation of yield. But this pattern had reduced with the crop forecast time leads; this is because the NCEP model gives almost near to mean values for maximum temperature and lower values for solar radiation. This led to decrease in the simulation of yield. But with improvement by WRF to some extent the yield simulation gets improved with increase in lead time.

At places where little over estimation of night temperature has occurred especially in upland plains, like Ludhiana, Sonipat, Patiala, Kaithal, etc. These places experiences a reduction in diurnal variation from NCEP and as well as from forecast. Thus an under prediction of yield with a magnitude ranging from 19% to 2 % occurred. Here also the WRF has shown improvement in the NCEP forecast thus leading to decrease in error with increasing lead times.

Districts like Karpurthala, Gurdaspur, Amritsar where the solar radiation is over predicted in WRF model shows a high over prediction in yield that increases with increase in forecast lead times. This is because solar radiation with NCEP is under predicting the real scenario (lowered yields) while the WRF model overestimates the solar radiation (higher yields).

Thus the variability of crop yield is at 11 %, 8 %, 6% and 3 % for the forecasts with lead times 7 days, 15 days, 30 days and 45 days respectively. Actually with same data source or with ensemble of actual weather, the crop yield must have decreased with increase in time, but here since the NCEP data is used as an ensemble with WRF, the former is found to have inaccuracies when compared with the latter, thus giving inversed results. The station data could have been interpolated but due to their scarce nature, the quality of the forecast would have still been not better for spatial forecast. The use of weather generator popular presently for crop forecasts might not be scientifically strong, since it gives a statistical comparison than a process based solution and also are data specific and can work atleast well only for the station location. An alternative of using WRF downscaled weather data for the remaining season could be used and tested for its efficiency.

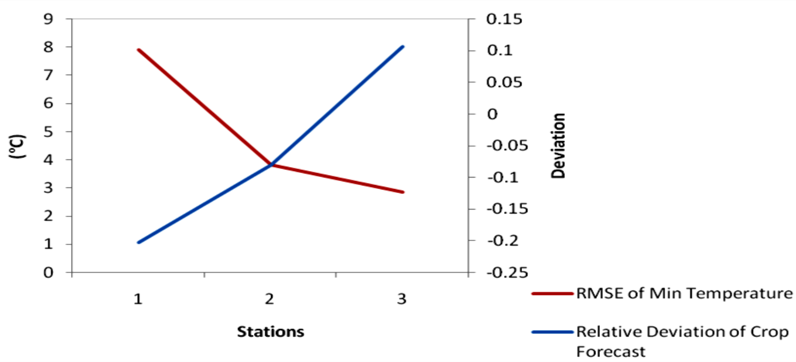


Fig.5.20-Demonstration of how an error in forecasting temperature propagates in forecasting crop model (Refer to station number from Appendix)

For first station the deviation of Maximum Temperature is higher in magnitude thus there is under prediction of yield by the crop model, for the second station the error gets reduced and thus the deviation in crop yield forecast is also reduced while for third the temperature is reduced to optimal condition where the over-prediction of the crop model occurs due to optimal lowering of maximum temperature.

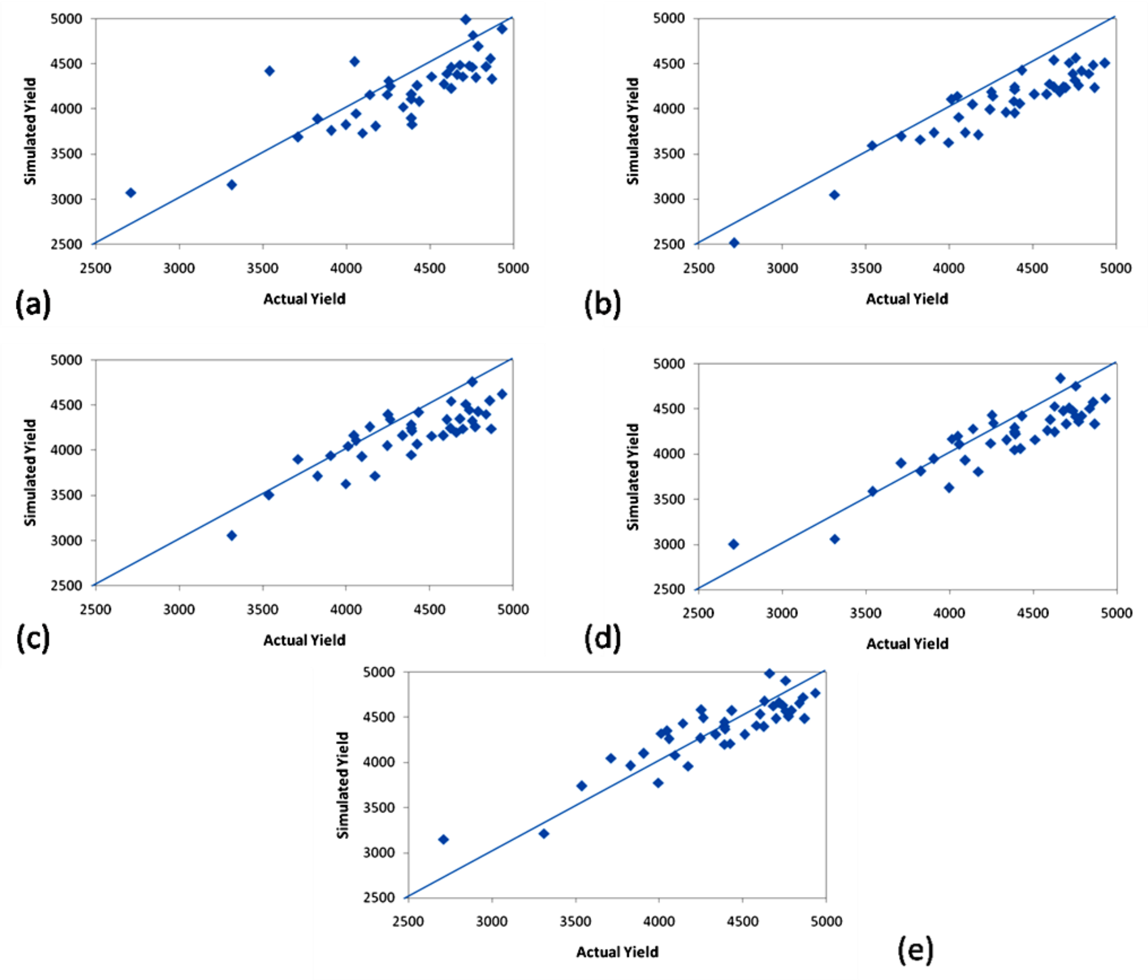


Fig.5.21-The scatter plot of different crop forecast cases with observed yield (spatial) (a) NCEP_estimate (b) NCEP+7days forecast (c) NCEP+15 days forecast (d) NCEP+30 days forecast (e)NCEP +45 days forecast. Units- Kg/Ha

Table 5.3 Averaged Statistics for the crop forecasts (spatial)

Forecast Case	Average Yield	RMSE	MAE	RD	MAPE	Agreement Index
F1(NCEP_full)	4224.37	354.30	279.43	-2.29	6.59	0.83
F2(NCEP+7day)	4069.86	324.87	284.89	-6.14	6.44	0.87
F3(NCEP+15day)	4128.39	298.18	251.86	-4.81	5.73	0.89
F4(NCEP+30day)	4194.84	255.90	221.61	-3.11	5.08	0.91
F5(NCEP+45day)	4345.58	208.65	179.45	0.41	4.29	0.94

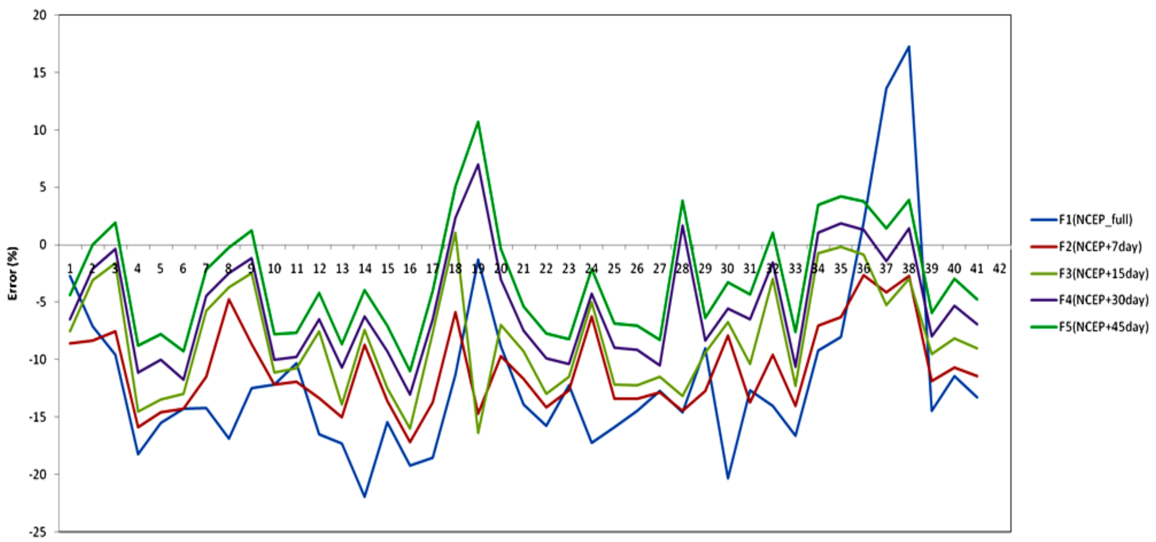


Fig.5.22-Relative Deviation of yield during different cases district wise

Table 5.2 Relative Error Deviation (%) district wise for multiple crop forecasts

S.No	District	**State**	F1	F2	F3	F4	F5
1	Mahendragarh	Haryana	-2.68272	-8.5959	-7.53906	-6.47538	-4.33911
2	Faridabad	Haryana	-7.09832	-8.33855	-3.11346	-2.10753	0.010774
3	Gurgaon	Haryana	-9.59164	-7.52528	-1.60903	-0.40416	1.959676
4	Rewari	Haryana	-18.2514	-15.8359	-14.5358	-11.1458	-8.73155
5	Jhajjar	Haryana	-15.4863	-14.578	-13.4588	-10.0344	-7.73946
6	Bhiwani	Haryana	-14.2649	-14.2781	-12.9737	-11.7666	-9.24539
7	Rohtak	Haryana	-14.2349	-11.4527	-5.7304	-4.43357	-2.13762
8	Sonipat	Haryana	-16.9016	-4.75231	-3.67837	-2.47871	-0.20658
9	Hisar	Haryana	-12.502	-8.6336	-2.45358	-1.20197	1.28069
10	Panipat	Haryana	-12.1837	-12.1636	-11.1079	-9.98722	-7.75387
11	Fatehabad	Haryana	-10.3225	-11.9298	-10.734	-9.75904	-7.65577
12	Jind	Haryana	-16.4889	-13.3554	-7.51849	-6.48094	-4.15906
13	Karnal	Haryana	-17.2821	-15.0138	-13.9234	-10.7107	-8.59993
14	Sirsa	Haryana	-21.9484	-8.68455	-7.44225	-6.21701	-3.92367
15	Kaithal	Haryana	-15.4348	-13.5459	-12.478	-9.24362	-7.04536
16	Kurukshetra	Haryana	-19.2295	-17.1614	-16.0298	-13.036	-10.9669
17	Yamunanagar	Haryana	-18.5451	-13.6912	-7.66753	-6.46608	-4.00585
18	Ambala	Haryana	-11.2892	-5.84959	1.055316	2.345191	5.059999
19	Panchkula	Haryana	-1.28351	-14.7165	-16.3812	6.976409	10.69262
38	Mewat	Haryana	-8.81097	-9.6813	-6.98328	-3.01181	-0.38119
40	Palwal	Haryana	-13.8986	-11.6631	-9.29126	-7.50384	-5.37847
20	Patiala	Punjab	-15.7385	-14.1595	-12.9596	-9.86495	-7.72049

21	Mansa	Punjab	-12.2589	-12.6478	-11.4849	-10.3714	-8.19354
22	Bathinda	Punjab	-17.2736	-6.22178	-5.01689	-4.26882	-2.09146
23	Muktsar	Punjab	-15.8651	-13.4167	-12.1499	-8.93185	-6.84902
24	Sangrur	Punjab	-14.4827	-13.3702	-12.2362	-9.14133	-7.02214
25	Fatehgarh Sahib	Punjab	-12.721	-12.8382	-11.5148	-10.5229	-8.24559
26	Faridkot	Punjab	-14.5605	-14.4691	-13.1496	1.663876	3.825355
27	Moga	Punjab	-9.03984	-12.6813	-9.37994	-8.35974	-6.31703
28	Ludhiana	Punjab	-20.3269	-7.87001	-6.75799	-5.57206	-3.27715
29	Firozpur	Punjab	-12.6833	-13.7135	-10.3528	-6.48495	-4.3327
30	Nawanshahr	Punjab	-14.0063	-9.53516	-2.97783	-1.52669	1.051269
31	Rupnagar	Punjab	-16.6298	-13.9824	-12.3057	-10.6023	-7.56137
32	Jalandhar	Punjab	-9.20441	-7.0457	-0.76175	1.020289	3.45378
33	Kapurthala	Punjab	-8.01407	-6.26512	-0.18397	1.825661	4.195052
34	Amritsar	Punjab	1.923991	-2.63175	-0.88301	1.269803	3.758601
35	Hoshiarpur	Punjab	13.64854	-4.12795	-5.26114	-1.43195	1.414798
36	Gurdaspur	Punjab	17.26738	-2.66399	-2.94811	1.408979	3.919483
37	Barnala	Punjab	-14.4358	-11.8724	-9.53498	-7.97819	-5.90617
39	Mohali	Punjab	-11.4131	-10.6949	-8.16372	-5.30931	-2.9371
41	Taran Taran	Punjab	-13.2661	-11.4168	-9.00435	-6.94542	-4.75724

5.9.3. Cross comparison of actual (MODIS LAI) against LAI from simulation experiments:

LAI is also validated against daily LAI obtained from simulation experiments. It gives similar agreement to that of yield. The validation with LAI is done to evaluate the models' performance in a spatial scale. The spatial forecasts are also compared with MODIS LAI and F5 *(NCEP+45 days)* gives a very good agreement throughout the growth stage and at most locations. On an average a deviation of about 12 % is observed throughout the growing season

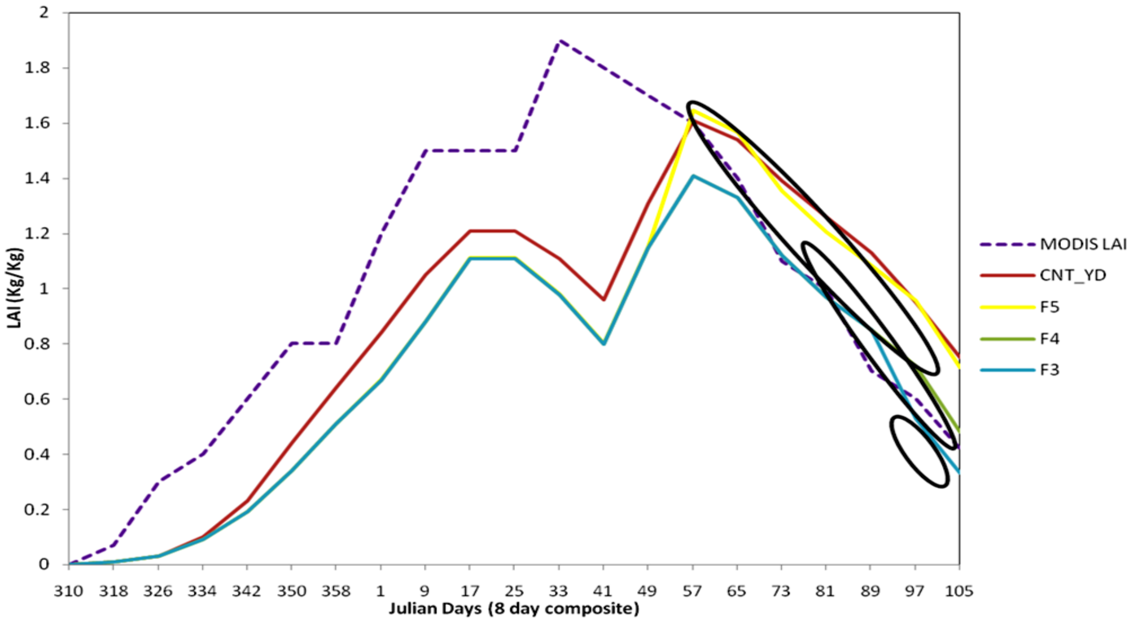


Fig.5.23-Comparing LAI simulation between significant forecasts and MODIS after calibration. The black circles indicate the impact of each case on the LAI

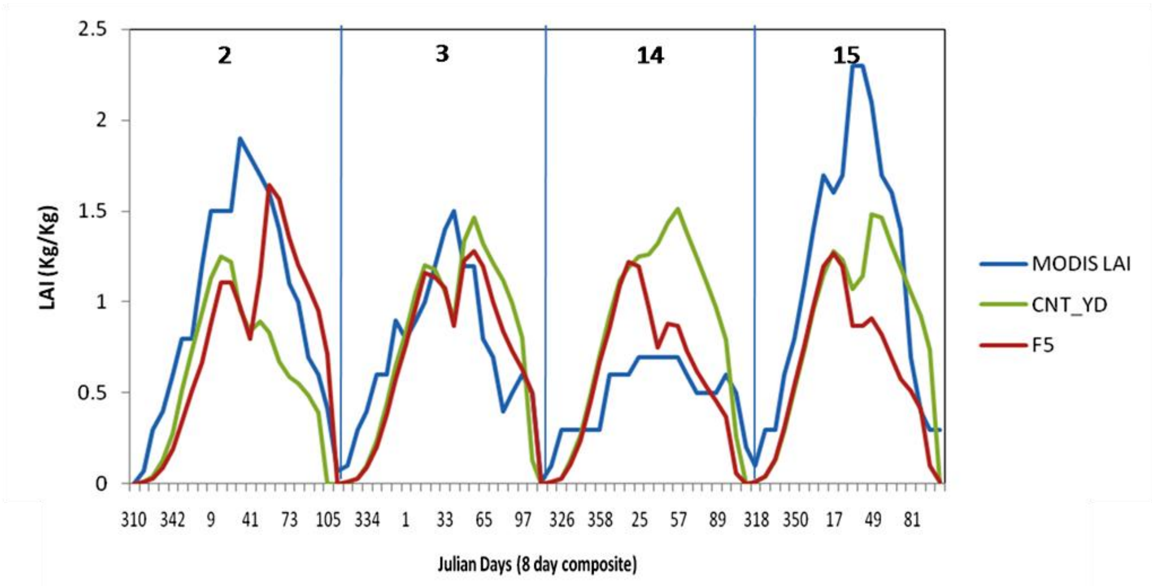


Fig.5.24-Comparing LAI simulation for CNT_YD, F5 with MODIS. The numbers marked above in the figure denotes stations for which the comparison is made. *(Refer to Appendix for the station details)*

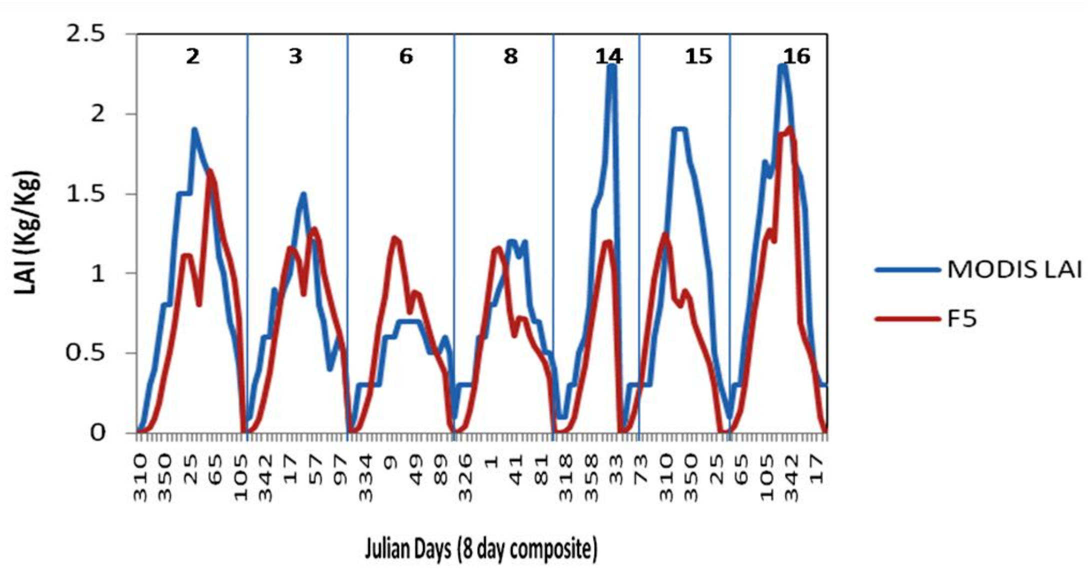


Fig.5.25- Graph showing the pattern of simulated LAI for F5 forecast with MODIS LAI. The numbers marked above in the figure denotes stations for which the comparison is made. *(Refer to Appendix for the station details)*

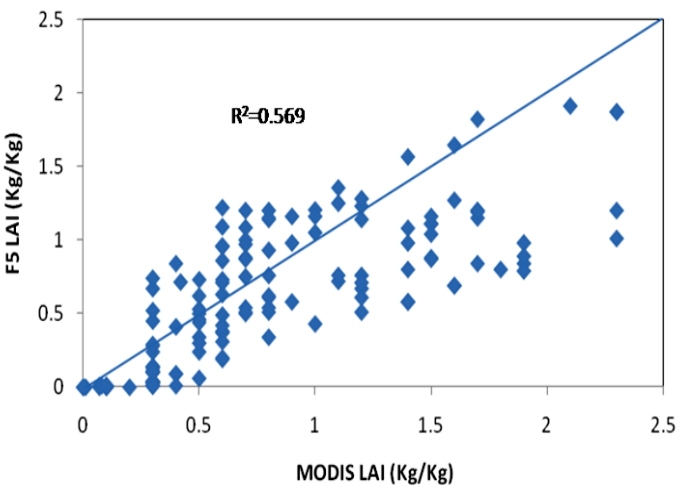


Fig.5.26- Right graph showing the correlation the forecast and MODIS LAI

Chapter 6

CONCLUSIONS AND RECOMMENDATIONS

The major objective of the project is to test the ability of an integrated approach for forecasting crop yield at various lead times with dependable accuracy. It emphasize mainly on incorporation of various kinds of models and informatics tools that enables development of agro meteorological information system and early warning system for food security analysis. The conclusions that are arrived from the project are compiled in the chapter. It also includes the recommendations and possible implications while using this methodology. The practical utility and the future scopes are highlighted to encourage the technology transfer and communicate science to practitioners/forecasters.

6.1.Weather Forecasts

In a complex modelling system like atmosphere, it is tough to explain the cause and effect relationship. From the discussion in previous section, it is clear that almost the weather variables are correlated to each other but in different degrees. In general, the main problem concerned with weather is its uncertainty, how well it can be predicted and with what degree of accuracy is a question to be answered. The doubling of errors happens when the magnitude of error becoming just double of it with progressing time. At extended forecasts this doubling occurs due to accumulation of errors, this becomes a limiting factor to state the efficiency of the forecast *(Lorenz, 1984)*. If the doubling occurs at faster rates, the forecast becomes soon irrelevant since the deviations are very high. For example the initial error in forecasting temperature maximum is 1.78 ° C; the double of the error is about 3.56° C which is near about reached at 30 days forecast. So the doubling time for the maximum temperature is 30 days. This gives a quantitative measurement of the error propagation and if the doubling time is less then the forecast for the period is stable to some extent. Here in the study, most errors with increasing lead times are from the shift of the forecast period from normal weather (March) to summer (April) were extremities are inevitable; due to error propagation the model is not able to capture this extremity with the magnitude evident at initial stages. Doubling time for most of the weather forecast is about to be 45 days (little less) for the simulation period. Although error propagation is present which is eminent with huge under estimation of pressure; the false alarms of rainfall, its progress is slow due to lower baroclinical and barotropical instability (extremities) and it is for the same reason why the doubling of error takes time. Surprisingly, some surface parameters like relative humidity and wind speed (compared with the observed data from NOAA), mainly in plains, the deviation has got reduced over the period. This is because even if the error is accumulating, the long forecasts have some stable simulation days for which the model prediction is almost matching. This encourages one that if the initial errors associated with the model (systematic errors), the initial global weather boundary data, the local initial conditions are improved then the forecasting is possible for a least disturbed season like winter even at extended time scales more than 45 days with acceptable degree of reliability.

Following conclusions can thus be arrived in regard with weather forecasting:

- The up gradation of the land surface parameters improved the models' performance of simulating temperature by 21%, solar radiation by 18%, precipitation by 5 %, relative humidity by 30%, wind speed by 12% and pressure by 4 %.
- The forecasts that are generated at multiple time scales had an overall root mean square ranging between 1.58° C to 5.05° C for maximum temperature 1.57° C to 4.14° C for minimum temperature, 3.19 MJm^{-2} to 4.07 MJm^{-2} for solar radiation, 2.3 ms^{-1} to 2.4 ms^{-1} for wind speed, 15% to 20 % for relative humidity and 0.4mm to 0.5mm for precipitation with higher root mean squared error values for the longest forecast. The weather variables that are forecasted showed an acceptable agreement even till 45 days, except for precipitation.
- The doubling effect of the error is slowly established since the forecast is finished for a less turbulent season.
- The WRF model doesn't suffer from major shock due to change in the dataset. It responds well to the change in the datasets.
- Global WRF aids in extending the forecast range from short to long ranges though is a new field of research.
- Error propagation increases with increase in the lead times due to accumulation.
- The quantum of the increase is associated with the complexity of the area under study. If it is more complex then the predictability gets degraded with increase in the range of forecast.
- Also the turbulence in the atmosphere plays a very vital role in deciding the longest meaningful forecast. For a season like winters were disturbances are low one can go for forecasting longer at acceptable accuracies.

6.2.Crop Forecasts

Crop forecasts at synoptic extent are achieved by transferring the weather forecasts at regional level to the crop model. To conclude, at point level the forecasts are no way inferior to the actual data at least in terms of the current study. Since the actual data itself has some inherent errors. If the actual station data with high integrity is used then theoretically, the forecast at lead times should decline in their efficiency with progress in time. But high integrity of the station data is a tough question to be answered. Also the error accumulation is not highly visible. Thus at point studies these forecasts might be very helpful to take complex decisions within season.

At spatial level, the forecasts are appreciable when compared with CNT_YD simulation. Even the 30 day and 45 day forecast has shown more skill than the usage of full length station data. This might have occurred due to the error in the station data, the point representation of the station data, data recorded at the station may or may not represent the conditions at the agricultural field. Leaving the fact that station data is erroneous; the forecast itself has good agreement with MODIS LAI which proves the capacity of this integrated system. The error has propagated, but slowly. The error in the weather variables has got converted to errors in yield assessment but as district aggregates, and on a regional level this propagation is barely noticeable which gives a positive sign for of these kind of methodologies for early warning systems.

The following conclusions were arrived in addition:

- The forecasted yields at point scale are able to capture 95% of variability. There is an increase in the deviation from actual yield as lead time increases, but at forecast times of 30 and 45 days, significant improvement of the yield forecast of about 1 % occurs due to replacement of missing and unrealistic weather variables in the station data.

- For the regional scenario, the ensemble forecasts of NCEP and WRF are utilized. The forecast at various time scales are combined with the NCEP and forecasts are generated. The forecasts are also good with the ability to capture of about 85% variability of yield on an average. The NCEP with 45 days weather forecast of WRF gave good results spatially with a hit score of about 92%. The WRF forecast showed an average improvement of 30 % over the NCEP data and thus the improvement of yield forecast with the increase in WRF inputs can thus be explained. The proliferation of error from weather forecast to crop forecast is slow, since the weather forecasts are to some extent consistent.

- Thus, wheat yield forecast is possible for multiple times (45 days at maximum) in prior with a coupled approach of weather model, crop model and Geomatics for a regional extent at 10km resolution with an average deviation ranging between 5 to 10 %.
- Forecasts are possible at 45 days, 30 days, 15 days and 7 days with an average deviation of 7 %, 10 %, 14% and 18% respectively.
- If the NCEP data would be replaced with WRF full season global model downscaled data the deviation might decrease.
- The lead time to issue crop forecast can be decided depending on the accuracies associated with weather forecasts.
- The error proliferation is present but the aggregates at district level have reduced the magnitude of the error.
- The complexity of the area and the dynamic nature of the season influence the yield prediction skills.
- The error occurs most in extremely high yield and extremely low yield conditions, this might be accounted to the semi-optimal conditions at which the spatial run is made.
- The study gives well agreed results thus concluding that the methodology is viable to be used for regional level forecasting and can be tested for various areas and crops.

6.3.Recommendations and Challenges

Weather forecasts are a long time challenge in the field of research. Ample techniques are available with no single best technique. Patrick Young stated “The trouble with weather forecasting is that it’s right too often for us to ignore it and wrong too often for us to rely on it”. This condition might change with the improvement in the understanding of the complex processes that govern the atmospheric behaviour. An unstable system can never be predicted well until the reasons influencing instability is well known. Yet approximations are always possible. Though not very accurate, known level of inaccuracies might also help. The main attention in weather forecasting is to identify and address the source of error. Two important sources are amplification and accumulation. Managing these sources to some extent might help to get an improved accuracy. The present study addresses the forecast, reducing the accumulation by defining appropriate initial conditions. Though the land surface parameters addressed here are most important, the horizontal component of landuse landcover, the vegetation fraction. The problem from bare soil evaporation and other fluxes relating to soil evaporation can be managed by adding the soil moisture inputs to the model. These are two other important parameters that one can add to improve the assimilation of land surface processes that influence the atmospheric behaviour. While using the weather model one should understand the limitations associated with the model and operate it. Like for example if the requirement is a coarser run, then using a high resolution input of 1 km will only create smoothening problems. The input can be upscaled using some external techniques that would not simply average but perform some statistically sound techniques to enhance the data even at coarser resolution. This way the data should be managed according to the requirement. Another important challenge in land surface modelling used at weather models is the sub-grid parameterization for landuse landcover and the elevation. This is a research question at recent times. Sub-grid variability would improve the process at each landuse land cover level and would improve the forecast viable for application based studies. The data assimilation in terms of assimilating the input land surface data by advanced techniques can be done. This might reduce the shock that the model undergoes that way improving the weather forecast. The full length WRF models' forecast can be tested in the crop model. The crop model runs in a semi-optimal mode, it can be more refined to represent the actual field conditions. The trend factor in the yield assessment is not considered in the project. A good hold on the extremities would exist if this factor is integrated along with the methodology. Assimilation can be done with the crop model to enhance the performance of the system. Here in the study the forecasts of the weather is consistent for even till 45 days and proved to be more useful in achieving better crop forecast than use of long-term normal weather data for forecast periods.. The error growth is slow thus making the season to be suitable for extended long range forecasts *(Zheng et al, 2013)*. Some generalisations have been used throughout the project to reduce the complexity level. Those generalizations have to be understood and if the complexity is worth handling for the particular application, then it can be incorporated. A trend factor can also be added to the integrated model so that the error due to extremities will be handled to some extent.

6.4.Implications of the study

The study has a wide area of applications. The value of the forecasts at various time scales and its usage is stated by *WMO, 2010*. The forecast would help to take timely and effective decisions on a regional scale. The key regulation parameters will include revised estimates of marketable surplus, changes in consumption behaviors, requirements for national food assistance programs, and the analyses of the domestic and international price transmissions. Accurate crop production forecasting can be used to make informed food policy decisions and to allow rapid response to emerging problems. The implication of the current analysis would be many folds but a check has to always be placed in utilizing the methodology in terms of quality.

6.5.Future scope

Future scopes of the project can be discussed as follows:

- An attempt can be made to create a complete decision support system to eliminate the complexities of inter-platforms and programming involved in the present study.
- Now that we knew the methodology works well, it can be extended to other seasons and other crops to test the utility in those cases.
- More sophisticated techniques like microwave remote sensing (to obtain images during kharif season) and data assimilation (for input data and refining of the outputs in both models) can be used to increase the usability and robustness of the methodology.
- Additional inputs from earth-observing satellites must be tested in both the models.
- The weather model should be tested for efficiency with assimilation of high frequency satellite derived weather parameters along with GCM outputs.
- The methodology can also be refined by adding block based sowing date information, cultivar information, soil database, crop cutting experiments, management practices. This could improve the models reach at national level.
- The study can be extended to develop early warning systems for drought/famine alarms, and high end agro-advisory services at state, district and block level.
- The project can be tested for its utility at farm level to increase its commercial and social impact.
- National level projects using this kind of methodology would definitely improve the level of forecast skill available presently in this field due to its scientific appeal.

"It is far better to foresee even with some level of uncertainty than not to foresee at all". This methodology is in its early stages. But has a wide applicability. The limitations should be understood and national level researches have to be continued in this aspect to handle the food security problem and societal development on a large scale.

Chapter 7

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APPENDIX

Appendix 1: Observatories used for validation of models.

S.No	Station	Lat (N)	Long (E)	Height (m)	Landuse
1	ISRO340_15F154(PRSC.PAcampus.Ludhiana)	30.90083	75.80028	237	Build up
2	ISRO342_15F156(RS.SF.PAU.Kapurthala)	31.39	75.35861	217	Double / Triple Cropping
3	ISRO343_15F157(KVK.Bahowal.Hoshiarpur)	31.38083	76.02417	313	Double / Triple Cropping
4	ISRO344_15F158(RRS.KandiArea.Balachaur. Nawan)	31.09583	76.38889	407	Kharif only
5	ISRO346_15F15A(KVK.PAUcomplex.HaveliKalan. Roopnagar)	30.97556	76.51722	330	Build up
6	ISRO347_15F15B(KVK.ShamerNagar. Eaterhgarhsahil)	30.62111	76.40556	271	Kharif only
7	ISRO348_15F15C(BRRS.Rahuri.Patiala)	30.34861	76.31861	253	Double / Triple Cropping
8	ISRO349_15F15D(SRS.PAUFarm.Kheri.Sangrur)	30.18639	75.87917	238	Double / Triple Cropping
9	ISRO350_15F15E(Agrometdept.PAUcampus. Ludhiana)	30.8975	75.80056	237	Build up
10	ISRO351_15F15F(KVK.PAUfarm.Samrala. Ludhiana)	30.83917	76.18222	267	Build up
11	ISRO352_15F160(KVK.BudhSinghwala.Moga)	30.7575	75.16222	219	Double / Triple Cropping
12	ISRO353_15F161(KVK.MallewalFarm.Ferozepur)	30.90944	74.6625	199	Double / Triple Cropping

13	ISRO354_15F162(RRS.PAUfarm.Abohar.Ferozpur)	30.17333	74.20778	191	Zaid only
14	ISRO355_15F163(RHSSFarm.Birsikhanwala. Faridkot)	30.64194	74.84306	205	Double / Triple Cropping
15	ISRO356_15F164(KVK.VPO.Goniana.Muktsar)	30.44528	74.50861	197	Rabi only
16	ISRO358_15F166(RS.DabwaliRoad.PAUFarm. Bathinda)	30.15889	74.92778	208	Other wasteland
17	Amritsar	31.64	74.86	234	Build up
18	Hissar	30.34	76.38	215	Build up
19	Patiala	29.15	75.7	350	Rabi only

* The first 16 stations are ISRO AWS observatories, the last three are obtained from Global Summary of a Day.

Appendix 2: Statistical Measures used to evaluate the models.

Measure Name	Formula	Significance
RMSE (root mean squared error)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i - o_i)^2}$	The RMSE serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. RMSE is a good measure of accuracy, but only to compare forecasting errors of different models for a particular variable and not between variables, as it is scale-dependent. (same units as the quantities measured)
MAE (mean absolute error)	$\frac{1}{N}\sum_{1}^{N}\lvert f_i - o_i\rvert$	The MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction. It measures accuracy for continuous variables. (same units as the quantities measured)

MAPE (mean absolute percent error)	$\frac{100}{N}\sum_{1}^{N}\left\lvert\frac{f_i - O_i}{O_i}\right\rvert$	It is used to compare the precision of different measurements on a non-directional basis.
Relative Deviation	$\left(\frac{f_i - O_i}{O_i}\right) * 100$	Relative error is useful for comparing the precision of different measurements. It also makes error propagation calculations much simpler.
Improvement factor	$\frac{\left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i^c - O_i)^2} - \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i^m - O_i)^2}\right)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i^c - O_i)^2}} * 100$	To compare between two models/ simulations. Similar to finding difference between RMSE's. (%)
Agreement index	$1 - \frac{\sum_{i=1}^{N}(f_i - O_i)^2}{\sum_i^n(\lvert f_i - \bar{x}\rvert + \lvert O_i - \bar{x}\rvert)^2}$	The index of how much the forecast agrees with the actual data. (in scale of 0 to 1)
Hit Score	$\frac{No\ of\ correct\ forecasts}{No\ of\ forecasts} * 100$	To measure the success of the forecast. (%)

Where,

f_i is the forecast at ith observation

O_i is the actual observed data at ith observation

N is the number of observations

f_i^c is the forecast of control run (WRF-CNT) at ith observation

f_i^m is the forecast of modified run (WRF-EXT) at ith observation

$\bar{x}$ is the mean of the observed values