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Application of Seasonal Temperature and Rainfall Forecast for Wheat Yield Prediction for Palampur, Himachal Pradesh

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Abstract

In this study, performance of seasonal temperature and rainfall forecast were evaluated for forecasting of wheat yield using CERES-wheat model for Himachal Pradesh region. Using the historical monthly total rainfall and mean maximum and minimum temperature values, 1000 daily weather realizations were generated using disaggregation technique. The moving average correlation between observed and generated weather sequences were calculated for different parameters viz., rainfall intensity, rainfall frequency and total monthly rainfall. The correlation values for all these parameters increased with the increase in number of weather realizations and attained its peak near 200 realizations. Thereafter, the correlation became almost constant which concluded that 200 weather realizations were optimum to know the behaviour of predicted weather sequences and its application in crop simulation models. The lead-1 temperature and rainfall forecast for November-April (6 months forecast), December-April (5 months forecast), January-April (4 months forecast), February-April (3 months forecast), March-April (2 months forecast) and monthly forecast of April month (1 month forecast) were generated for 1984-2008 in hindcast mode using multi-model ensemble technique. The monthly and seasonal forecasts were converted into daily weather sequences using the stochastic disaggregation technique. For each generated forecast, observed weather was merged with the respective forecast to make it entire season weather observations so that it can be used in crop models. CERES-wheat model was calibrated and validated for variety HPW-89 for Palampur region and the genetic coefficients thus generated were used to simulate the wheat yield in different years starting from 1984-2008. It was found that six month forecast i.e. October start November-April did not have significant skill and it failed to capture the variation in wheat yield for different years. However, with the advancement of season thereby reducing the period of forecast, the forecast skill improved progressively. It was also observed that 3 or 4 months seasonal forecast have almost similar results with a slight variation. However, forecast for three months or lesser period was able to simulate the wheat yield in an efficient manner.

Keywords: wheat; monthly and seasonal forecast; stochastic disaggregation; crop simulation model.

1. Introduction

The weather variability is regarded as the major culprit of year-to-year fluctuations in crop yields (Krishna Kumar et.al, 2004). A seasonal forecast refers to a forecast for average temperature and precipitation for comparatively a longer duration i.e. few months. The primary goal of the seasonal forecast is to characterize the climate for the upcoming months in comparison to similar period in previous years. There can be a number of climate forecasts depending upon the length and lead time period of the forecast that may range from few days to several months. However, the degree of forecast uncertainty increases with the advancement of lead time duration of the forecast. Seasonal forecasts can significantly contribute to food and livelihood security by providing advance information with sufficient lead time to adjust critical agricultural (e.g., irrigation, weed control, planting, harvesting) decisions (Apipattanavis et al., 2010). Seasonal has great potential to improve agricultural production, food security and livelihoods particularly in areas where changes in precipitation and intensification of extreme weather events are expected with long-term climate change (Roncoli et al., 2009). It can help farmers to take intelligent decisions about proper selection of crops, date of crop sowing/ planting and crop preventive measures to maximize the crop yields so that they can get benefit from good seasons and minimize the adverse effect of climate for their crops (Cabrera et al., 2009).

A crop model needs a season-long daily weather dataset to simulate a crop yield. A skillful seasonal forecast in a monthly or seasonal average sense is necessary.

However, only mean values does not guarantee a good crop yield forecast (Baigorria et al. 2007). Operational climate season forecast generally focus on seasonal mean rainfall while crop models are usually designed to assimilate daily rainfall values. Therefore, establishment of linkage between climate forecasts with the crop simulation model can be a valuable tool for prediction of crop productivity for a season as well as to investigate suitable strategic options for crop management and food security. Several researchers (Tomei et al, 2009, Ines et al, 2011) have used rainfall forecasts from different global circulation models (GCMs) for its application in crop simulation models with promising results.

Grain yield prediction using a crop simulation model requires weather input for entire growing season. When the availability of weather information is limited for certain period only, it becomes necessary to generate 'synthetic weather' for the remaining part of the season. This deficiency can be fulfilled by use of stochastic weather generator (Hansen and Ines, 2005).

The economy of the Himachal Pradesh depends to a great extent on agriculture and horticulture - the highly climate-sensitive sectors contributing 20.1% of the total Gross State Domestic Product. The average annual rainfall of Himachal is 1111 mm. The dominant features of hill farming in Himachal Pradesh are largely dry /rainfed farming. Climate risk management through seasonal forecasts would be more appropriate in climate vulnerable areas of the State. India is one of the major wheat producing and consuming countries of the world. It is the major staple food crop grown widely in Rabi season in the Himachal Pradesh. The main reason of incorporating temperature forecast additionally is that production of wheat crop fluctuates due to fluctuation of temperature during January, February and March. The temperature during February and March months are the most crucial in this region to decide wheat yields due to its crucial role in flowering and grain development stages.

Keeping these facts in mind, wheat yield estimation was done in this study with the help of seasonal forecast using stochastic disaggregation technique to generate daily weather sequences for wheat growing season of Palampur District, Himachal Pradesh, India. Different combination of observed and disaggregated weather sequences have been used to reproduce wheat yields and the performance of the forecast has been tested.

2. Materials and Methods

2.1 Models used for generating seasonal forecast

In this study we used temperature and rainfall forecast from the Multi Model Ensemble Technique described by Acharya et al. (2011). The eight different AGCM/ AOGCM MODEL outputs downloaded from International Research Institute for Climate and Society (IRI), Columbia, USA were used to generate the seasonal forecast for wheat growing season (November-April) for the Himachal Pradesh region. First, the forecast was generated for entire wheat growing season (November-April) i.e. six month period. Further, with the advancement of each month, the forecast for remaining months of the growing season was generated. We used lead-1 forecast of the model for rainfall and temperature for October start November-April (NDJFM), November start December-April (DJFMA), December start January-April (JFMA), January start February-April (FMA), February start March-April (MA) and March start April as shown in table-1. Accordingly for NDJFMA, DJFMA, JFMA, FMA, MA and April, the duration of forecast period was six, five, four, three, two and one month respectively. A single value for seasonal forecast was obtained for each season of all the years. Monthly values were generated from the seasonal forecasts on the basis of climatology based rainfall distribution among different months.

2.2 Stochastic disaggregation model

An iterative approach as described in Hansen and Indeje (2004) was used to generate stochastic rainfall sequences that match monthly predicted rainfall totals with ± 5 % accuracy. The stochastic weather generator described by Hansen and Mavromatis (2001) has been used in this paper which was developed with the aim to generate stochastic realizations of synthetic weather with reliable inter-annual variability. For each predicted values, 1000 weather sequences were generated using this weather generator.

2.3 Crop simulation model

Total eight seasons actual field observations conducted at C.S.K. Himachal Pradesh Agricultural University Palampur, Himachal Pradesh were used to calibrate and validate the CERES- wheat model to derive the genetic coefficients. The experimental site is located at 32.6° N latitude, 76.3° E longitude and at an altitude of about 1300 m above the mean sea level. The average annual rainfall of the area is around 2100-2200 mm. The average temperature is around 26°C during wheat cropping season (rainy season) and 14°C during wheat cropping season (winter). We used CERES-wheat model from DSSAT Version 4.5 (Hoogenboom et al., 2010) to simulate growth and yield for the wheat variety HPW-89. Required inputs include daily weather data (minimum and maximum temperature, rainfall and solar radiation), soil properties, initial soil water content, cultivar characteristics, planting date and spatial arrangement, and irrigation and N fertilizer management. We compared yields simulated with observed daily weather data and yields simulated with disaggregated historic monthly rainfall totals for Palampur region. Each crop simulation scenario used a single weather station, soil profile description and set of management practices, based on existing data sets and publications.

3. Results and Discussions

3.1 Comparison of yields simulated from disaggregated daily rainfall and temperature based on observed mean temperature and rainfall forecasts

Daily weather sequences with the stochastic disaggregation were generated using the climatological means of temperature alone, rainfall alone and temperature and rainfall both. These weather sequences were used to simulate the wheat yields. The mean values of the simulated and observed yield were then compared to know their performance. Using the rainfall alone as a predictor showed good performance in wheat yield prediction. However, combination of Temperature and rainfall was found very successful for prediction of wheat yield with very high correlation coefficient (0.90) and least RMSE (i.e. 252.06) [Table 1]. Therefore, combination of rainfall and temperature were used to analyze the forecast performance for subsequent analysis and application in this manuscript.

3.2 Yields simulated from disaggregated seasonal rainfall forecast

Different forecast as described were used to simulate the wheat yield for different season of the wheat crop. The forecast data was merged with observed weather data with the advancement of each month. Thus generated weather observations were used to run the CERES-wheat model for prediction of wheat yield for different years of observations.

3.2.1 Performance of Temperature + rainfall forecast for wheat yield prediction in different years

The comparison between observed and simulated yield is shown in the Table 1. It was observed that when only total rainfall was used as a predictor to generate the daily weather sequences, it incorporated a lot of noise in the data and therefore it failed to predict the wheat yield correctly (Fig. 1a). However, the combination of mean temperature and total rainfall as a predictor was found most efficient to be used in crop model for wheat yield prediction (Fig. 1b). The variation of wheat yield for different forecast period viz., November-April (6 months forecast), December-April (5 months forecast), January-April (4 months forecast), February-April (3 months forecast), March-April (2 months forecast) and monthly forecast of April month (1 month forecast) has been shown in Fig. 2. It is evident from here that 6 month forecast failed to show any significant skill for its application in crop simulation model. In general, performance of forecast was improved as the forecast period was reduced and observed period was increased. The correlation values between observed and simulated yields were increased progressively with the advancement of each month. However, no prominent variation was observed between the simulated yield of DJFMA and JFMA i.e. 5 and 4 months forecast period. After the February month, the crop growing period was very near to complete and therefore very high correlations were for found during March-April and April period. Similarly, root mean square error (RMSE) values also showed a decreasing trend with the advancement of each month i.e. shortening the forecast period. The RMSE values were found highest for NDJFMA and lowest when only single month forecast along with 5 months observation values were used (Table 1).

Table 1: Comparison between wheat yields predicted from observed monthly values of rainfall and temperature + rainfall.

Forecast Predictor	Observed monthly mean Forecast		
	Corr. Coeff.	Std. Dev	RMSE
Rainfall	0.82	492.46	311.54
Temperature + Rainfall	0.90	501.57	252.06
NDJFMA	0.01	283.83	3069.5
DJFMA	0.51	314.74	2354.3
JFMA	0.85	560.31	1483.0
FMA	0.82	480.36	1569.7
MA	0.97	544.11	640.9
April	0.99	561.08	466.6

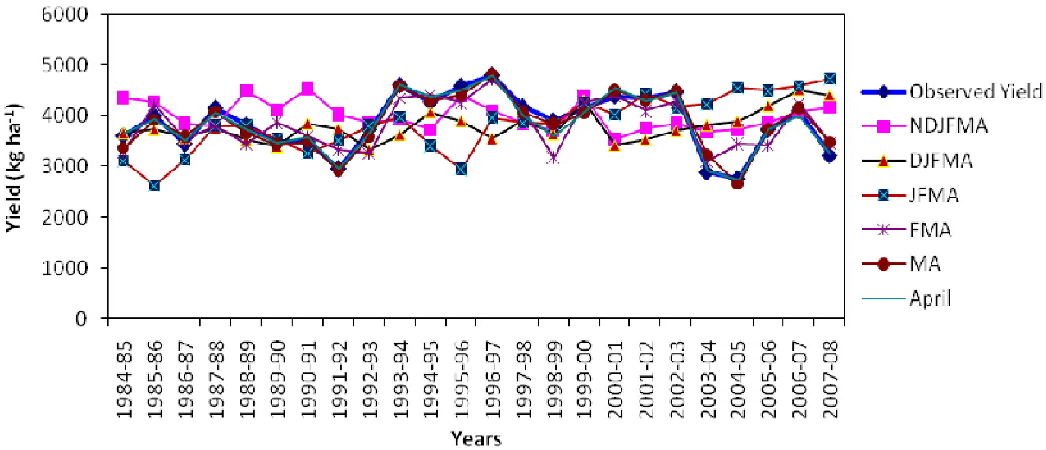

Figure 2a: Wheat yield estimation using predicted weather scenario and disaggregated historical weather scenario using the forecast of different seasons i.e. Nov-April, Dec-April, Jan-April, Feb-April, Mar-April and for April only.

4. Conclusions

Results from the seasonal and monthly forecasts of rainfall in crop yield modelling suggest that reliable crop yield predictions can be obtained using an ensemble multi-model system forecast. The use of ensemble seasonal forecast as well as monthly forecast of rainfall for crop yield estimation demonstrated that useful information can be obtained through the probability associated to the yield forecast.

The accuracy of seasonal rainfall forecast (in terms of simulated grain yields over observed) was increased as the number of leading month's forecast reduced. Greater variations were accounted in over-predicted years than a tendency to under-predicted years in simulated grain yields (obtained from seasonal as well as monthly rainfall forecast with different leads) over observed. Over-prediction in simulated grain yields were found in low yielding years, whenever, under-prediction in higher yielding years. Simulated grain yields (obtained by using seasonal as well as monthly rainfall forecast) showed substantially lower RMSE over observed, as the number of realizations increased.

The use of GCM-based seasonal and monthly rainfall forecasts with crop simulation model to predict yields and to evaluate potential management responses was the main application that motivated this study. Disaggregation of observed stations as well as rainfall forecast data in a realistic manner is a promising area of future research that may greatly enhance the utility of stochastic disaggregation for impact studies. In order to further improvement in crop yield predictions there is need to improve climate forecast that can predict rainfall frequency and amount precisely.

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