Prediction of Kharif cotton yield over Parbhani, Maharashtra: Combination of extended range forecast and DSSAT-CROPGRO-Cotton model

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ABSTRACT. Cotton is one of the major crops cultivated in Parbhani district and it is a major cash crop to the Marathwada region. Cotton cultivation in this region is facing severe challenges due to an increase in the frequency of droughts, monsoon variability and dry spells during critical growth stages of crop. Use of seasonal forecast products extended range forecast system (ERFS) in crop models is investigated for improving the seed cotton yield prediction skill for the ensuing monsoon season at Parbhani in Maharashtra. A stochastic disaggregation is used to downscale seasonal and monthly forecast products in daily weather sequences. These weather series are taken as input in the Decision Support System for Agro technology Transfer (DSSAT) Cropping System Model (CSM) CROPGRO-Cotton model for the crop yield prediction at different stages of forecast: June-September (4 month forecast), July-September (3 month forecast), August-September (2 month forecast) and monthly forecast for September (1 month forecast) and correlation between observed versus disaggregated monthly frequency and intensity of rainfall for June, July, August and September.
Crop productivity estimated with a reliable seasonal climate forecast using a dynamic crop model for a forthcoming crop-growing season, before the season actually starts, will help farmers and planners considerably to prepare for the crop-growing season (Jones et al., 2000 and Hansen, 2002). This study may be useful to guide about sensitivity of the particular sub-season/month forecast on the yield of cotton crop and beneficial to farmers or crop planners to climatic risk and economic importance of crop specifically in rainfed area, the study was proposed to take appropriate intervention to minimize the climatic risk in cotton for Parbhani district using DSSAT V4.6 model.

2. Materials and method

2.1. Study area

Parbhani district is situated in the Godavari drainage basin in the central part of the India. The area is lying on the central part of Marathwada region in Maharashtra. It comes under semi-arid. The geographic location of the site (Parbhani) is 18° 45' to 20° 10' N, latitude; 76° 13' 77° 39' E, Longitude 457.5 meters above mean sea level (MSL) in Marathwada division of Maharashtra state. It has an average annual rainfall of 938.7 mm, from June to September during south-west monsoon. The remaining rainfall is received during post-monsoon period from October to December (North-East monsoon).

In methodology it is consisted that the collection of historical weather and crop data. The data was collected from All India Coordinated Project on Agrometeorology, (AICRPAM), Observatory, VNMKV, Parbhani. The required weather parameter data like Maximum temperature ($T_{\text{max}}$), Minimum temperature ($T_{\text{min}}$), Bright Sunshine Hours (BSS), Rainfall (RF) was used as a basic input data for run the DSSAT V4.6 model. The daily weather data recorded at the Meteorological observatory, AICRP on Agrometeorology, VNMKV, Parbhani (Latitude 19° 16' N, Longitude 76° 47' E and Altitude 430 m MSL) from 1980 to 2017 (38 years) was utilized in this study. In addition to that also seasonal forecast data of 38 year was collected from India meteorological department (IMD), New Delhi and Indian Institute of Technology (IIT), Bhubaneswar.
TABLE 1

| S. No. | Observed data          | Forecast data          |
|--------|------------------------|------------------------|
| 1.     | Jan - May & Oct - Dec  | JJAS (Jun, Jul, Aug, Sep) |
| 2.     | Jan - Jun & Oct - Dec  | JAS (Jul, Aug, Sep)    |
| 3.     | Jun - Jul & Oct - Dec  | AS (Aug, Sep)          |
| 4.     | Jun - Aug & Oct - Dec  | S (Sep)                |

The risk associated with the crop and prediction of the yield of cotton crop was done by using DSSAT V 4.6 version model. For running the DSSAT model, daily weather data, soil properties and initial soil condition, information on crop cultivar and crop management data was required.

2.2. Crop simulation model

2.2.1. DSSAT model

The Decision Support System for Agro technology Transfer (DSSAT) model is a cropping system model package, comprising over 28 Cropping Systems Models (CSMs) (Hoogenboom et al., 2010) and it is widely used to simulate crop growth, development and yield on a daily basis (Hoogenboom et al., 2010).

The skill of disaggregated ERFS monthly/seasonal products as compared to observed rainfall in respect of frequency and intensity at different realization has been generated and discussed. The findings indicate the usability of output from the stochastic disaggregation. Therefore the output from the disaggregated monthly/seasonal forecast product is taken as the input for the model. Initially, the DSSAT model can run using observed data from January-May and the disaggregated forecast for June-September, which will further updated by incorporating the observed daily sequence for the month of June (forecast for July-September) likewise with the advancement of each month of the growing season (Table 1). We can take forecast in sequence like in Table 1.

From the seasonal rainfall forecasts (ERFS products), daily weather scenarios are generated using stochastic disaggregation. These daily ERFS forecasted data and IMD daily observed data was used for crop modeling. At first, the CERES-cotton simulation models was developed using IMD daily observed weather data separately for hind cast mode (1980-2017) and real time mode (1980-2017). The yield simulated using IMD daily observed data is considered as a baseline yield for comparison and evaluation of predicted cotton yield by using ERFS forecasts. The cotton yield is also simulated using ERFS seasonal (JJAS) and sub-seasonal (JAS, AS and September) rainfall forecasts in hind cast and real time mode. The climatological mean, standard deviation (SD) and coefficient of variation (CV) are calculated for baseline and ERFS forecasted (seasonal and sub-seasonal) yields for hind cast and real time. Thus the detail concept of DSSAT-CSM (Crop Simulation Model) has given below flow chart.

2.3. Statistical evaluation/Validation of model

Before any model can be used with confidence, adequate validation or assessment of the magnitude of the errors that may result from its use should be performed. Model validation, in its simplest form is a comparison between simulated and observed values. Several statistical measures are available to evaluate the association between predicted and observed values. Several statistical measures are available to evaluate the association between predicted and observed values. The summary measures describe the quality of simulation while, the difference measures try to locate and quantify the errors.

The latter include the mean absolute error (MAE), the mean bias error (MBE) and the root mean square error (RMSE). They were calculated according to Willmott (1982) as follows and were based on the terms \((P_i - O_i)\):

\[\text{(i) Mean Bias Error (MBE)} = \frac{1}{N} \sum_{i=1}^{N} (P_i - O_i)\]

\[\text{(ii) Root Mean Square Error (RMSE)} = \left[\frac{1}{N} \sum (f_i - O_i)^2\right]^{1/2}\]

\[\text{(iii) Error} = \frac{\text{[predicted - observed]}}{\text{observed}} \times 100\]

\[\text{(iv) Percent Error (PE)} = \frac{\text{RMSE}}{\text{O}} \times 100\]
where, P - Predicted yield, O - Observed data yield and N - no. of years.

3. Results and discussion

3.1. Disaggregated daily observed rainfall

Stochastic disaggregation works on the concept of adjusting the rainfall frequency and intensity in order to achieve the monthly/seasonal rainfall total as a target. The rainfall statistics as reproduced by stochastic disaggregation for the period June to September is shown in Figs. 1 to 3 respectively. The correlations between observed and disaggregated realizations for intensity and frequency of rainfall, for individual months as well as for the monsoon season as a whole (June to September) shown considerable variation among individual realizations. The correlation value corresponding to the rainfall intensity shows a continuous increase with the number of realizations and reaches an almost constant
value at around 200 realizations. Rainfall intensity was best reproduced during the month of July (correlation coefficient = 0.89). The maximum correlation attained for the months of June, August and September were 0.84, 0.81 and 0.57, respectively (Fig. 1). These correlation values are found to be statistically significant at the 99% significance level. Similarly, the rainfall frequency of the disaggregated rainfall sequences was evaluated against observed values. The maximum correlation values were attained at around 200 realizations, which are 0.66, 0.74, 0.56 and 0.70, corresponding to the months of June, July, August and September, respectively (Fig. 1). It was noticed that the statistical skill was lowest for the month of August during which the rainfall amount and occurrence frequency is found to be maximum (Fig. 2). Furthermore, the statistical skill of disaggregated realizations for seasonal frequency and intensity is evaluated and shown in Fig. 2. The correlation value for the whole season also increases with the increase in number of realizations (attains its maximum at around 200 realizations). Correlation of seasonal frequency of rainfall approaches a maximum of 0.71, whereas that of seasonal intensity was nearly 0.84 (Fig. 3). Variation in correlations of these parameters among realizations occurs due to variability of distribution in rainfall associated with the stochastic model.

3.2. Cotton yield simulated with disaggregated observed rainfall

The cotton yield produced by the crop model was validated against observation in view of some of the statistical measures such as correlation, mean bias error (MBE) and coefficient of variance (CV) standard deviation (SD), RMSE & PE. Disaggregated daily rainfall by the stochastic disaggregation method using observed mean monthly rainfall has the ability to reproduce yields simulated from observed rainfall. The ability improves asymptotically with the increase in number of realizations (Ines and Hansen, 2006). Cotton yields were simulated with CERES-cotton model using 200 weather series generated from stochastic disaggregation and observed weather over the area of interest as inputs (Parbhani) for the period 1980-2017. A time series of simulated cotton yield corresponding to each realization as well as to the observed weather is depicted in Fig. 4. It is found that the simulated cotton productivity corresponding to the realizations. From the stochastic disaggregation is in good agreement in most of the cases with the simulated cotton yield from observed daily sequences (Fig. 5). The average of simulated yield so fall the realizations is also evaluated and presented along with the observation in the Fig. 4. During 1997, the simulated crop yield with generated weather was considerably higher (0.648 t ha⁻¹) as compared to the yield with observed weather (0.377 t ha⁻¹). (Fig. 4). The mean and inter-annual variability in predicted cotton crop yield was in close agreement in most of the year with that of the observed yield. On the other hand the RMSE between the two number series was found to be 0.15 t ha⁻¹, which is in favor of low MBE (0.001 t ha⁻¹) (Table 2). In continuation, the two series is also evaluated in terms of correlation and PE. It is clear from the figure that the year-to-year variation is simulated well; this is also reflected in the high value of correlation (0.715) and PE 26.40 variation in cotton yield.
3.3. Cotton yield estimation using ERFS weather data of rainfed condition

The prediction skill for the cotton crop is evaluated by incorporating the disaggregated monthly/seasonal forecast product of four, three, two and one month in place of disaggregated observed sequence. The skill of disaggregated ERFS monthly/seasonal products as compared to observed rainfall in respect of frequency and intensity at different realizations has been discussed earlier (Figs. 6-13). Initially, the crop model was run using observed weather data for January-May and the disaggregated forecast for June-September, which was further updated by incorporating the observed daily sequence for the month of June (forecast for July-September), July (forecast for August-September) and August (forecast for September) with the advancement of each month of the crop-growing season.
3.4. Four (4) month ERFS (Jun to Sep) under rainfed condition

Cotton yield prediction was made using four (4) month ERFS product (June to September) under rainfed condition. The results are summarized and presented in Figs. 6 & 7. The predicted cotton yield improved as the season advances and inter-annual variation was well captured at all-time steps (Fig. 6). In particular, during the year 1986 and 2015, the yield was highly underestimated at all-time steps. Some of the statistical skill measures such as Correlation (0.671**), MBE (0.002) and RMSE (0.18) (Table 3) was found during June-September month disaggregated forecast values. The MBE did not show much variation among weather sequences, as the mean was almost captured at all the steps. An
improvement in these skills is noticed with the advancement of the season (Table 3). Incorporation of ERFS weather data in the updates of successive months, uncertainty in the prediction of yield diminished.

3.5. Cotton yield estimation using three (3) month ERFS (JAS) under rainfed condition

The end of June updated the four month ERFS by incorporating the observed daily sequence for the month of June and forecast for July - September and observed weather over the area of interest as inputs (Parbhani) for the period 1980-2017. The results are summarized and presented in Figs. 8 & 9 and Table 4. Results show that the simulated cotton productivity corresponding to the realizations (Fig. 9). From the stochastic disaggregation was in good agreement in most of the cases with the simulated cotton yield from observed daily sequences. During 1980 the simulated crop yield with generated weather was considerably higher (0.602 t ha\(^{-1}\)) as compared to the yield with observed weather (0.329 t ha\(^{-1}\)). Some of the statistical skill measures such as RMSE between the two number series were found to be 0.17 t ha\(^{-1}\), which was in favor of low MBE (0.001 t ha\(^{-1}\)). In continuation, the two series was also evaluated in terms of correlation and PE. It is clear that the year-to-year variation is simulated well; this is also reflected in the high value of correlation (0.678**) and PE 29.9. (Table 4). The similar study was found by Pal et al., 2013.

3.6. Cotton yield estimation using two (2) month ERFS (AS) under rainfed condition

The three month data by incorporating the observed daily sequence for the month of July ERFS updated to forecast for August-September and cotton yields were simulated from stochastic disaggregation of two (2) month ERFS (AS) and observed weather for the period 1980-2017. The results indicate that the simulated cotton yield corresponding to the 200 realizations (Figs. 10 & 11) and Table 5. From the stochastic disaggregation is variable agreement in most of the cases with the simulated cotton yield from observed daily sequences. During 1990 the simulated crop yield with generated weather was considerably higher (0.723 t ha\(^{-1}\)) as compared to the yield with observed weather (0.286 t ha\(^{-1}\)). The simulated cotton

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**TABLE 2**

| Yield SD CV R MAE MBE RMSE PE | OMY 0.568 0.22 38.3 0.715** 0.01 0.01 0.15 26.40 |
|-----------------------------|-----------------|
| PMY 0.577 0.12 21.5         |                 |

**TABLE 3**

| Yield SD CV R MAE MBE RMSE PE | OMY 0.568 0.22 38.3 0.671** 0.002 0.002 0.18 31.7 |
|-----------------------------|-----------------|
| PMY 0.636 0.11 17.2         |                 |

**TABLE 4**

| Yield SD CV R MAE MBE RMSE PE | OMY 0.568 0.22 38.3 0.678** 0.001 0.001 0.17 29.9 |
|-----------------------------|-----------------|
| PMY 0.621 0.11 18.4         |                 |

**TABLE 5**

| Yield SD CV R MAE MBE RMSE PE | OMY 0.568 0.22 38.3 0.728 0.003 0.003 0.21 37.0 |
|-----------------------------|-----------------|
| PMY 0.667 0.11 16.0         |                 |

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Fig. 10. Cotton yield estimation using two month (AS) ERFS weather data and predicted weather scenario of different years
of yield in 1991 and 2015 showed much reduced yield because the actual rainfall received in that two year was very less as compared to the normal. Some of the statistical skill measures such as Correlation (0.728**), MBE (0.003) and RMSE (0.21) (Table 5) was found to be August-September month disaggregated forecast values.

3.7. Cotton yield estimation using one (1) month ERFS (September) under rainfed condition

The end of August month updated the two month ERFS by incorporating the observed daily sequence and cotton yields were simulated from stochastic disaggregation of one (1) month ERFS (S) and observed...
TABLE 6
The cotton yield estimation using one month (S) ERFS weather data and predicted weather scenario of different years

|      | Yield | SD | CV | R  | MAE | MBE | RMSE | PE |
|------|-------|----|----|----|-----|-----|------|----|
| OMY  | 0.568 | 0.22| 38.3| 0.768** | 0.002 | 0.002 | 0.20 | 35.2 |
| PMY  | 0.648 | 0.11| 16.7| 0.768** | 0.002 | 0.002 | 0.20 | 35.2 |

weather for the period 1980-2017. The results are summarized and presented in Figs. 12 & 13 and Table 6. From the stochastic disaggregation was in good agreement in most of the cases with the simulated cotton yield from observed daily sequences. During 1990 the simulated crop yield with generated weather was considerably higher (0.687 t ha⁻¹) as compared to the yield with observed weather (0.286 t ha⁻¹). The year 1991, 1992 and 2015 showed much reduced yield because the actual rainfall received was less in that three year. On the other hand the RMSE between the two number series was found to be 0.20 t ha⁻¹, which is in favor of low MBE (0.002 t ha⁻¹). (Table 6) this is also reflected in the high value of correlation (0.768) and PE 35.2.

4. Conclusions

The historical weather data was analyzed with respect to prediction of the yield of cotton crop by using DSSAT V.4.6 model. The prediction skill of each multi-model ensemble (MME) along with the final unified model was found to be significant at the majority of the region during all monsoon months as well as for the season as a whole. Daily sequences of disaggregated weather scenarios from ERFS forecasts were in close agreement with the observed daily weather data for hind cast mode. The correlations between disaggregated ERFS weather sequences for JJAS, JAS, AS and September with observed daily data for seasonal total were 0.671, 0.678, 0.728 and 0.768, respectively. These correlations were increased with increase in incorporation of observed weather information. The climatological mean of predicted yield using the JJAS, JAS, AS, and September rainfall forecasts of ERFS was close to the mean baseline yield for the hind cast period (1980-2017). However, the values of the mean predicted yield for JJAS were (0.636 t/ha), JAS (0.621 t/ha), AS (0.667 t/ha) and September (0.648 t/ha). From the analysis of RMSE, it was found that the predicted yields from the JJAS and JAS ERFS forecasts have more error than those from the AS and September forecasts. However, the correlation coefficient was increased in ascending order with incorporation of observed weather data (JJAS < JAS < AS < September). Moreover, these skill scores were significant at the 90% confidence level. The standard deviation and coefficient of variation of predicted yield by using forecast was near to baseline yield while under predicted using the JJAS, JAS, and AS forecasts.

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