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

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सार – परभणी जिले में की जाने वाली खेती की प्रमुख फसलों में से कपास एक है, और यह मराठवाड़ा क्षेत्र की एक प्रमुख नकदी फसल है। सूखे की आवृत्ति में वृद्धि, मॉनसून परिवर्तनशीलता और फसल के महत्वपूर्ण विकास चरणों के दौरान शुष्क काल के कारण इस क्षेत्र में कपास की खेती को गंभीर चुनौतियों का सामना करना पड़ रहा है। महाराष्ट्र के परभणी में आगामी मॉनसून के मौसम के लिए कपास के बीज की उपज के पूर्वानुमान कौशल में सुधार के लिए फसल मॉडल में ऋतुनिष्ठ पूर्वानुमान उत्पादों के विस्तृत अवधि पूर्वानुमान प्रणाली (ERFS) के उपयोग की जांच की गई है। दैनिक मौसम अनुक्रमों में ऋतुनिष्ठ और मासिक पूर्वानुमान उत्पादों को कम करने के लिए एक प्रसंभाव्य विपुंजन का उपयोग किया गया है। इन मौसम श्रृंखलाओं को पूर्वानुमान के विभिन्न चरण में फसल उपज पूर्वानुमान के लिए कृषि प्रौद्योगिकी हस्तांतरण की निर्णय समर्थन प्रणाली (DSSAT) को फसल प्रणाली मॉडल (CSM) क्रॉपग्रो-कपास मॉडल के लिए इनपुट के रूप में लिया गया हैः जून-सितंबर (4 महीने का पूर्वानुमान), जुलाई -सितंबर (3 महीने का पूर्वानुमान), अगस्त-सितंबर (2 महीने का पूर्वानुमान) और सितंबर के लिए मासिक पूर्वानुमान (1 महीने का पूर्वानुमान)और मासिक आवृत्ति की तुलना में प्रेक्षित किए गए सहसंबंध (R) तथा जून, जुलाई, अगस्त और सितंबर में वर्षा की तीव्रता को 1980 से 2017 तक की प्रसंभाव्य प्राप्तियों (1000) में एक संख्या के रूप में लिया गया है। ऐतिहासिक उपज के डेटा में तकनीकी प्रवृत्ति से बचने के लिए, ERFS के पूर्वानुमानों का उपयोग करके अनुकारी उपज का मूल्यांकन करने के लिए प्रेक्षित मौसम डेटा के साथ अनुकारी उपज को बेंचमार्क (प्रेक्षित बीज कपास उपज) के रूप में उपयोग किया गया है। प्रेक्षित उपज के साथ अनुमानित उपज के सत्यापन के बाद सूखे के वर्षों की पहचान और कपास की पैदावार बढ़ाने के लिए महत्वपूर्ण विकास चरणों में विशेष हस्तक्षेप किए गए। प्राप्त निष्कर्ष परभणी में प्रेक्षित बीज कपास की पैदावार में साल-दर-साल परिवर्तनशीलता को समझने के लिए पूर्वानुमान उत्पादों की दक्षता की सिफारिश करते हैं। वर्षा की तीव्रता के अनुरूप सहसंबंध मान की संख्या के साथ निरंतर वृद्धि दिखाई और लगभग 200 प्राप्तियों पर स्थिर मान के करीब पहुंच गया। जुलाई के महीने में वर्षा की तीव्रता में सबसे अधिक वृद्धि हुई (सहसंबंध गुणांक = 0.89)। जून, अगस्त और सितंबर के महीनों में हुए अधिकतम सहसंबंध क्रमशः लगभग 0.84, 0.81 और 0.57 थे। ये परिणाम कपास की बुवाई के साथ-साथ फसल उगाने के मौसम के विभिन्न चरणों के दौरान प्रबंधन की अन्य जानकारी, हस्तक्षेप और कृषि गतिविधियों के लिए अग्रिम निर्णय लेने हेतु उपयोगी हैं।

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

as a function of the number of stochastic realizations (1000) from 1980 to 2017 was undertaken. To avoid a technological trend in historical yield data, yields simulated with observed weather data have been used as the benchmark (observed seed cotton yield) to evaluate the yields simulated using ERFS forecasts. Identification of drought years after the validation of predicted yield with observed yield and special interventions was made at critical growth stages to enhance the yield of cotton. The findings recommend the efficiency of forecast products to capture year-to-year variability in observed seed cotton yield at parbhani. The correlation value corresponding to the rainfall intensity showed a continuous increase with the number of realizations and reached an almost constant value at around 200 realizations. Rainfall intensity was best reproduced during the month of July (correlation co-efficient = 0.89). The maximum correlation attained for the months of June, August and September were ~0.84, 0.81 and 0.57, respectively. The outcomes are useful for taking decisions well in advance for sowing of cotton as well as for other input management, interventions and farm activities during different stages of the crop growing season.

Key words – Stochastic disaggregation, Crop simulation models, Seasonal/monthly rainfall forecast, Cotton.

1. Introduction

Cotton (*Gossypium spp.)* is one of the important cash/fibre crop of India which is tropical/subtropical crop grown in an area with rainfall of 600 mm to 2500 mm. At least 500 mm (20 inch) of water (rainfall/irrigation) is required to produce a cotton crop during the season in a constant and regular pattern (Doorenbos and Pruitt, 1984). In India, the crop occupies more than 9.2 m.ha. and its share in world cotton area is 27 percent. Total area of cotton in Maharashtra is 42.86 lakh ha, production 88.22 lakh bale and productivity 349.9 kg lint/ha. While the area in the Marathwada region is 15.07 lakh ha, production 33.0 lakh bale and productivity is 358 kg lint/ha. The area in Parbhani district is 1.99 lakh ha, production 3.98 lakh bale and productivity 339 kg lint /ha (Anonymous, 2020). The climate of Marathwada experiences wide intra district variability; about 80% of annual rainfall is concentrated between the months of June to September. The Aurangabad and Jalna experiences moist climate during rainy season, cold and dry during winter season, while Beed district experiences humid climate during rainy season, hot and dry conditions during rest of the part of the year. Nanded, Osmanabad, Latur, Parbhani and recently established Hingoli district are climatically very hot summer and cool in winter (Dakhore *et al.*, 2017).

Crop productivity may be predicted, by linking climate (seasonal) forecast to a crop yield model, at the beginning of the season or even long before the season starts, however, a skillful seasonal forecast does not mean that there will always be a good crop yield forecast, as a climate forecast gives a single value for the whole season. The Crop Estimation through Resource and Environment Synthesis (CERES)-crop is such a model having dynamic simulation processes for simulating crop yield. This is a process-oriented and management level model (DSSAT), for growth and development to the crop (Singh *et al.*, 1993), developed for predicting the growth duration, average growth rates and yield of crop.

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 rain fed area, the study was proposed to take appropriate intervention to minimize the climatic risk in cotton for parbhani district using DSSAT V4.6model.

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 Maximuma temperature (*T*max), Minimum temperature (*T*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

Observed data and forecast data

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
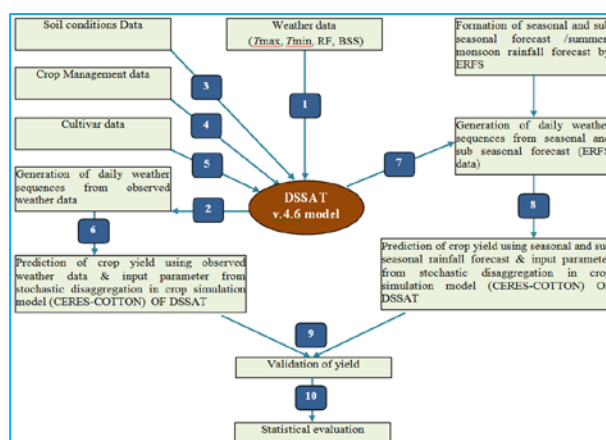
Flow chart

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. 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):

(*i*) Mean Bias Error (MBE) : $\sum_{i=1}^{n}\left(P_i - O_i\right)$

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

(*iii*) Error % : [(predicted – observed) / observed] $\times$ 100

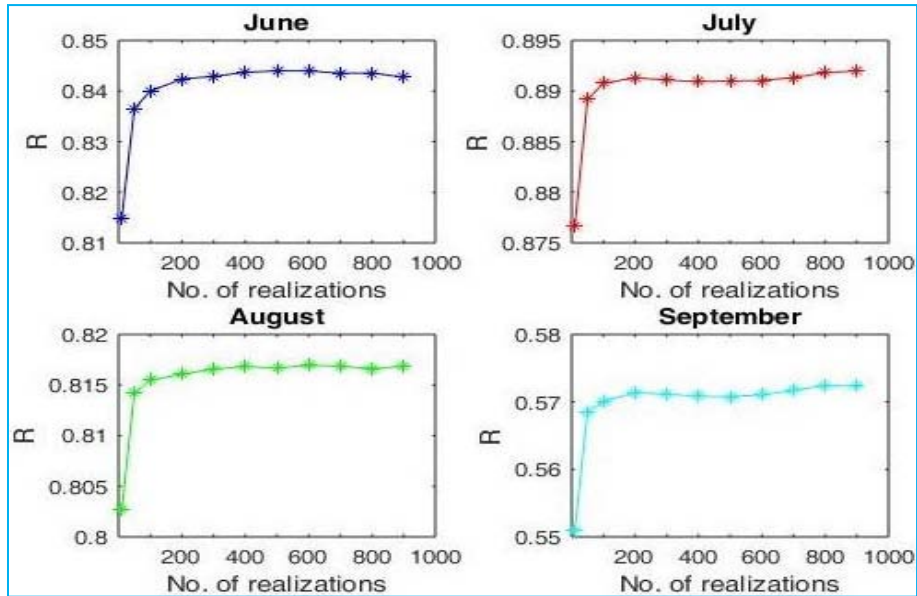(*iv*) Percent Error (PE) : RMSE / O $\times$ 100

Fig. 1. Correlation (R) between observed *versus* disaggregated monthly intensity of rainfall for June, July, August & September as a function of the number of stochastic realizations (1000) from 1980 to 2017
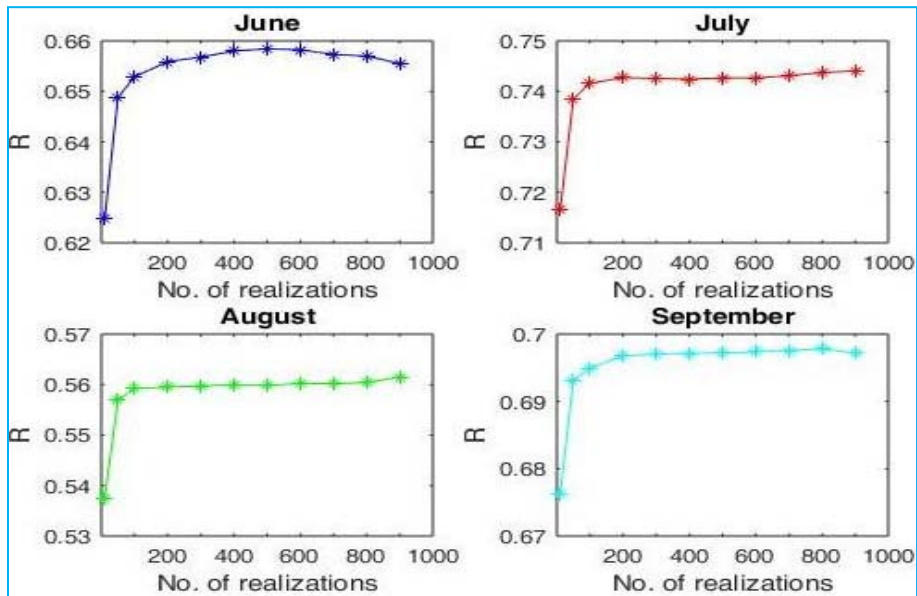

Fig. 2. Correlation (R) between observed *versus* disaggregated monthly frequency of rainfall for June, July, August & September as a function of the number of stochastic realizations (1000) from 1980 to 2017

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
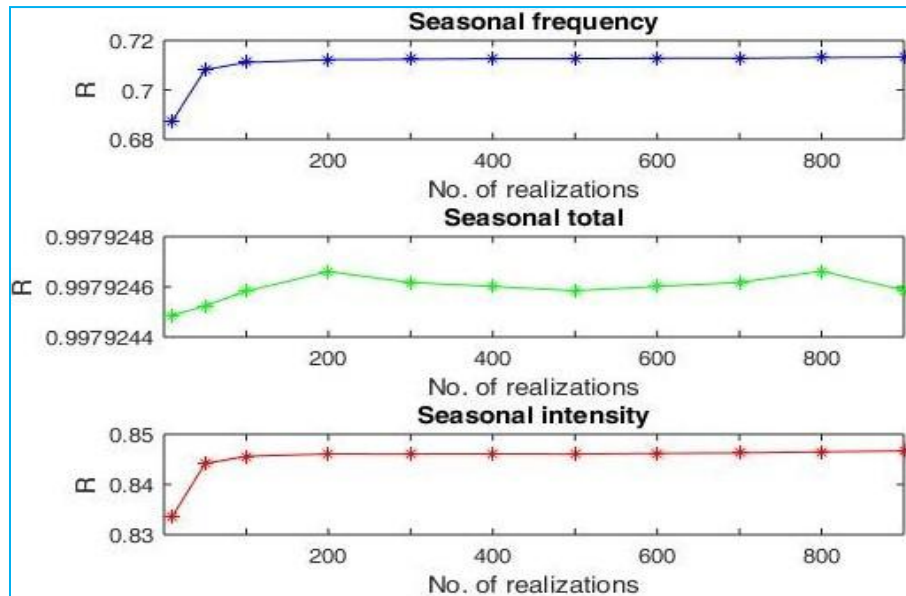
Fig. 3. Correlation (R) between observed versus disaggregated seasonal frequency and seasonal intensity of rainfall as a function of the number of stochastic realizations (1000) from 1980 to 2017

value at around 200 realizations. Rainfall intensity was best reproduced during the month of July (correlation co-efficient = 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.
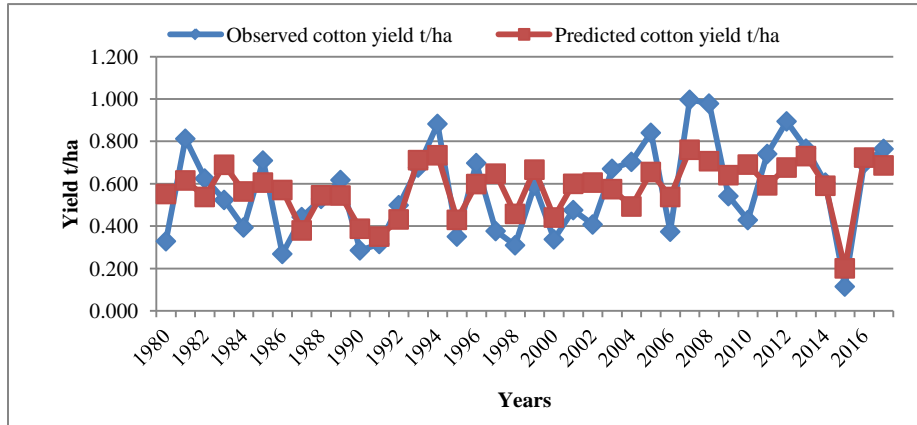
Fig. 4. Cotton yield estimation using observed historical weather data and predicted weather scenario of different years
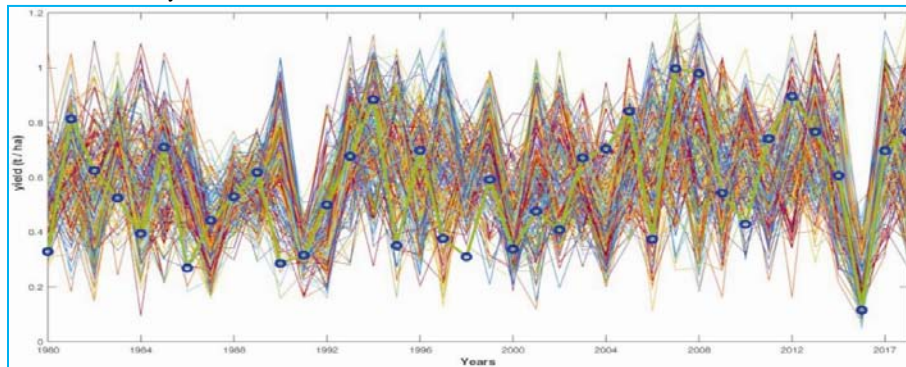

Fig. 5. Predicted yields using 200 realizations based on disaggregated observe data (38 year) under rainfed condition
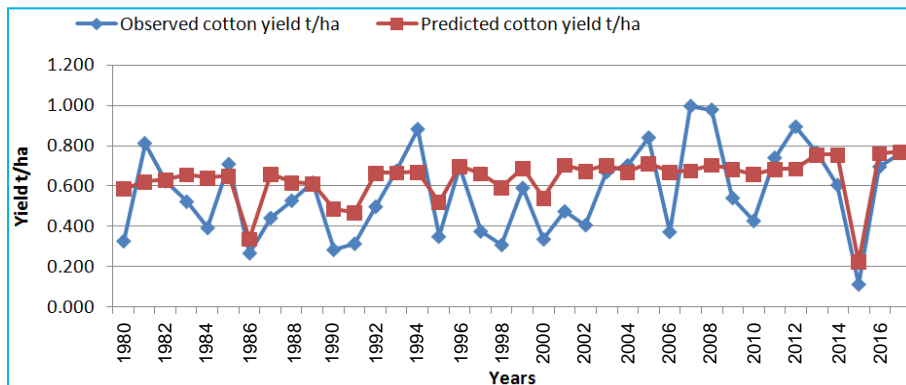

Fig. 6. Cotton yield estimation using four month (JJAS) ERFS weather data and predicted weather scenario of different years

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.
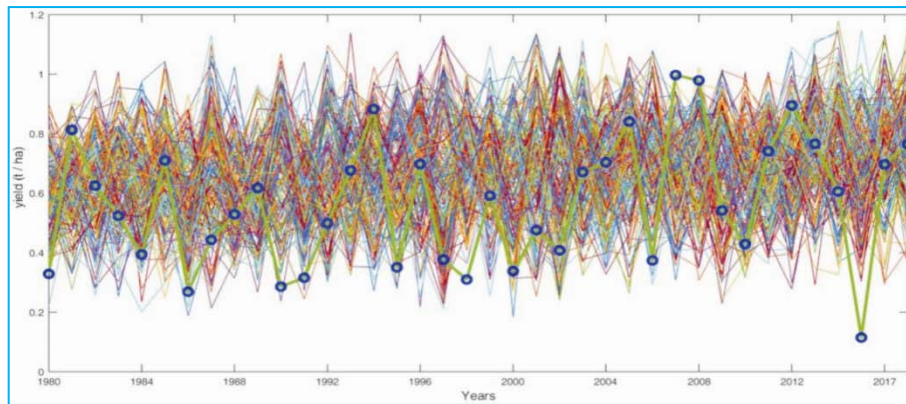
Fig. 7. Predicted yields using 200 realizations based on disaggregated 4 month ERFS (JJAS) (38 year) with under rainfed condition
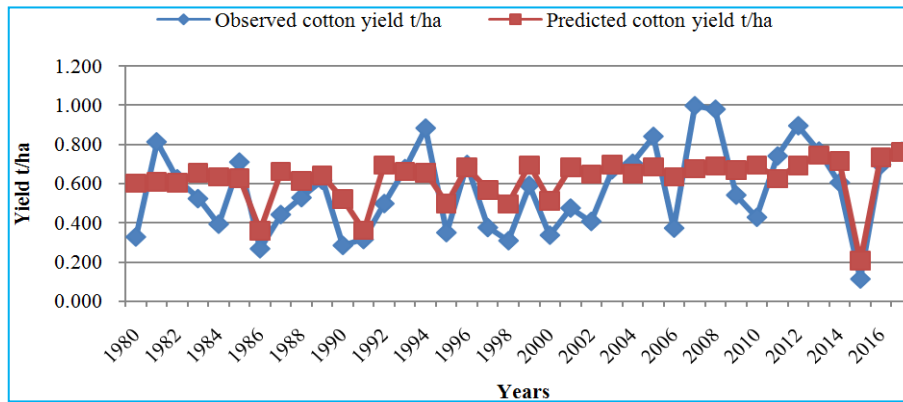

Fig. 8. Cotton yield estimation using three month (JAS) ERFS weather data and predicted weather scenario of different years
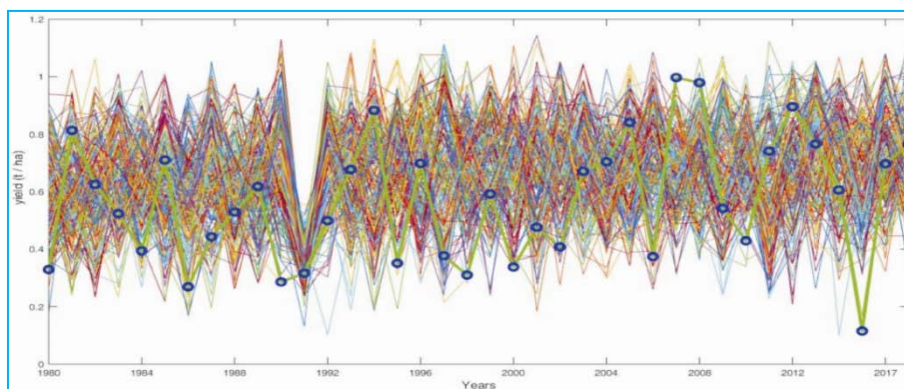

Fig. 9. Predicted yields using 200 realizations based on disaggregated 3 month ERFS (JAS) (38 year) with under rainfed condition

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
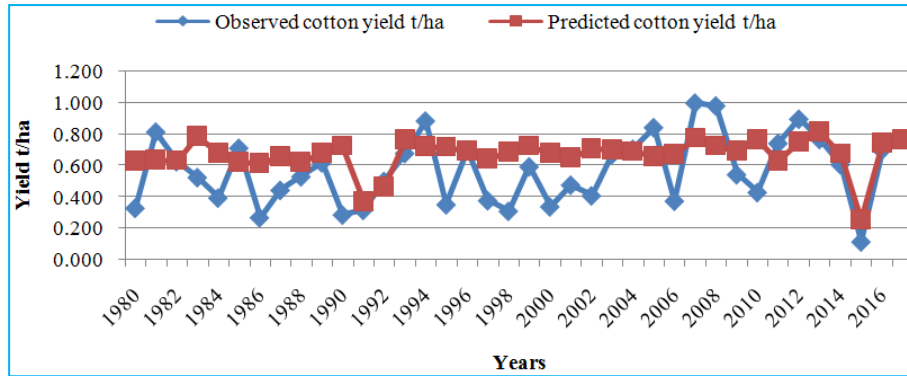
Fig. 10. Cotton yield estimation using two month (AS) ERFS weather data and predicted weather scenario of different years

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

TABLE 2

Test cotton yield estimation using observed historical weather data and predicted weather scenario of different years

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

TABLE 3

The cotton yield estimation using four month (JJAS) 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	0.671**	0.002	0.002	0.18	31.7
PMY	0.636	0.11	17.2					

TABLE 4

The cotton yield estimation using three month (JAS) 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	0.678**	0.001	0.001	0.17	29.9
PMY	0.621	0.11	18.4					

TABLE 5

The cotton yield estimation using two month (AS) 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	0.728	0.003	0.003	0.21	37.0
PMY	0.667	0.11	16.0					

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
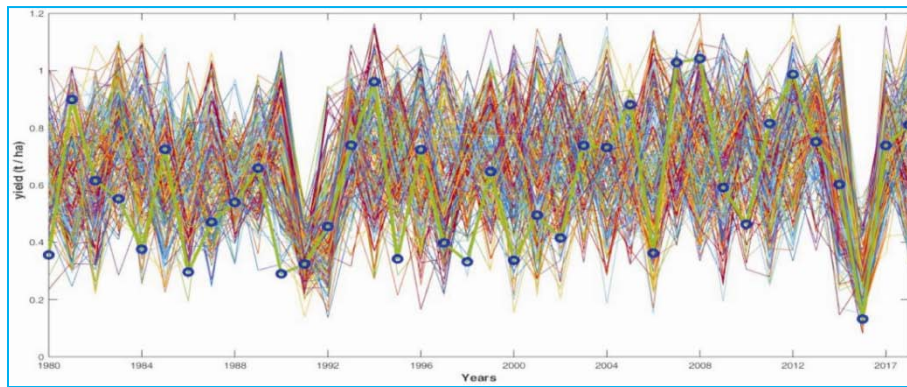
Fig. 11. Predicted yields using 200 realizations based on disaggregated two (2) months ERFS (AS) (38 year) with under rainfed condition
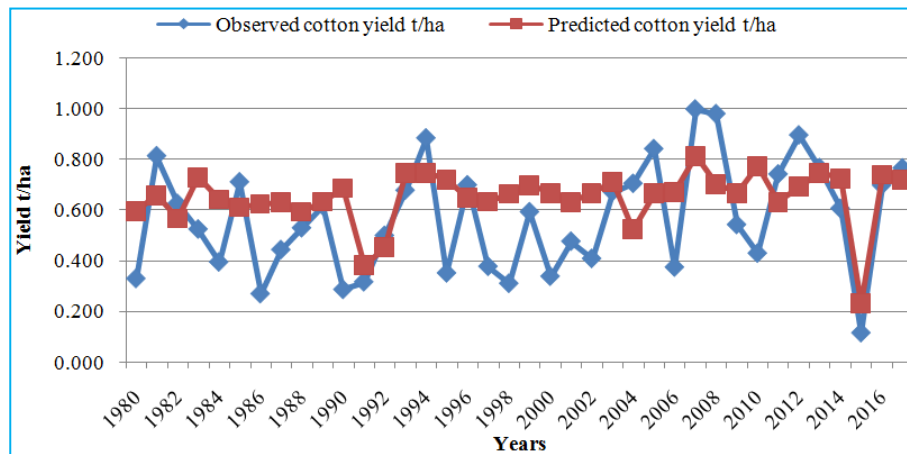

Fig. 12. Cotton yield estimation using one month (S) ERFS weather data and predicted weather scenario of different years
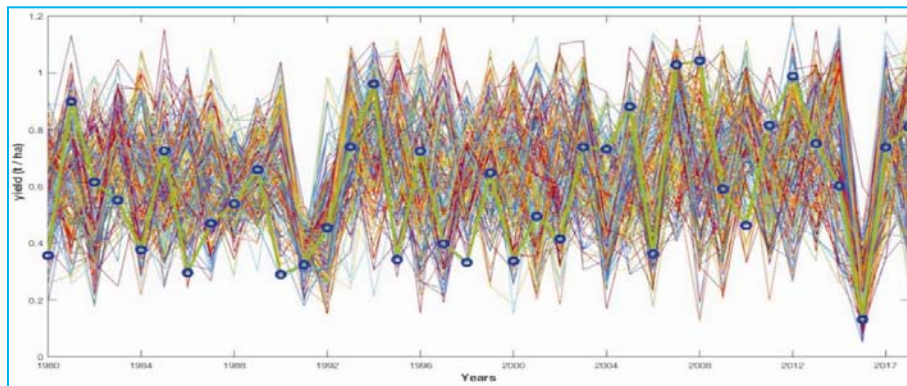

Fig. 13. Predicted yields using 200 realizations based on disaggregated 1 month ERFS (S) (38 year) with under rainfed condition

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

	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					

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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