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Impact of climate on oilseed production in Andhra Pradesh: A case study to understand regional level influences

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ABSTRACT

Oilseeds play an important role next to food grains in the Indian agricultural economy both in terms of area and production and India holds a significant share in world production too. The influence of climate change on oilseed production was not understood properly to devise resilience strategies in order to uphold the production and productivity. An attempt was made in this paper to understand the influence of climate change on oilseed production at a regional level using Andhra Pradesh as a case study through regression analysis as well as artificial neural networks (ANN). The results indicated that the predicted changes of climate on oilseed crops varied greatly by crop and region. The implications of regression and ANN models in predicting the climate change impact on different oilseed crops in Andhra Pradesh is discussed in detail.

Key words: Oilseeds, regional climate change, abiotic variables, ANN

India is one of the major oilseed producing country in the world and the main cultivated oilseeds are groundnut (*Arachis hypogaea* L.), *soybean (Glycine max L.),* rape seed (*Brassica napus* L.), mustard (*Brassica nigra* L.), sunflower (*Heliantus annuus* L.), sesame (*Sesamum indicum* L.) and Niger (*Guizotia abyssinica* L.). Oilseeds are the second largest agricultural commodity in India after cereals occupying 13-14% of gross cropped area. Oilseeds are being cultivated in an area of 27.22 million ha, with a production of 32.48 million tonnes with a productivity of 1193 kg ha^{-1} (2010-11) accounting for 1.4% of gross domestic product (GDP). Vegetable oils also contribute 1.5 to 1.7% of national exports and about 15-17% of the agricultural exports of the country (2006-07) (Hegde, 2007). Usually the oilseeds are grown under rainfed conditions in marginal soils. Considering the oilseeds output in 2008-09 as 27.72 million tonnes, the country needs to almost double the oilseeds production in the next 10 years requiring an annual growth rate of nearly 6% which will be a tall order, requiring efforts much beyond what is being ostensibly pursued until now (Hegde, 2007).

In recent past, research studies have reported that the impact of climate change on agriculture could result in problems related to food security and may threaten the livelihood activities upon which much of the population depends. Climate change can affect crop yields (both positively and negatively), as well as the types of crops that can be grown in certain areas. Usually, oilseed yields depend on many factors including genetic, environmental and agronomic factors as well as the interaction between them (Sidlauskas *et.al.,* 2003). There have been several studies of the effects of temperature/ precipitation rate on growth and development of oilseeds (Thurling, *et al.,* 1977, Mendham, *et al.,* 1981, Morrison, *et al.*, 1989). In this area numerous studies were carried out for predicting the growth rate/ production of oil seeds using conceptual as well as physical-based models and these models have practical limitations as several inter-related variables are involved (Heyi Wang *et al.*, 2011). Recently, soft computing tools like Artificial Neural Networks (ANNs), a general-purpose model with a limited set of variables have been used increasingly in various fields of science and technology for prediction purposes (Gail, *et al.,* 2002) particularly for nonlinear time series events over conventional simulation methods (Guan *et al.,* 2004).

Under the current circumstances, examining the vulnerability of oil seeds production to climate change and to determine regional impact of climate change is need of the hour. In this study, an attempt was made to predict regional climate change influence on oilseeds production viz., groundnut, castor, sesame, sunflower, safflower in Andhra Pradesh (AP) through regression and ANN's.

MATERIALS AND METHODS

For this study, the meteorological data (maximum temperature-^{0}C, minimum temperature-^{0}C, mean temperature-^{0}C and rainfall-CRF mm), district-wise (Adilabad-ADB, Anantapur-ATP, Kurnool-KUR, Mahaboobnagar-MNR, Nizamabad-NZB, Rangareddy-RR, Chittoor-CTR, Cuddapah-CDP, Karimnagar-KRN, Nalgonda-NLD, Nellore-NLR, Prakasam-PKS, Guntur-GNT, Khammam-KHM, Visakhapatnam-VSK, Vizianagaram-

VZM, West Godavari-WG) area under cultivation and production data (from 1990 to 2010) were obtained from various sources viz., India Meteorological Department (IMD), Directorate of Economics and Statistics, Govt. of Andhra Pradesh and Indian stats.com. The districts viz., ATP, CDP, KUR, MBN, CTR, NLR comprised the sourthern AP and the districts viz., ADB, RR, NZB, PKS, NLD, KRN constituted northern AP for data analysis and interpretation.

Data analysis

The data were subjected to traditional correlation and regression analysis as first line of support to understand the climate change influence on oilseed production in Toto. We attempted to test the ability of the ANN to predict the regional climate change influences with combinations of input variables at random by the suitable ANN program as second line of support. In the present case study, Elman Neural Network (ENN) was applied (details may be found in Elman, 1990).

Structure of neural network model

In a simple ENN structure (Fig.1), after the hidden units are calculated, their values are used to compute the output of the network and further, all are stored as 'extra inputs' called

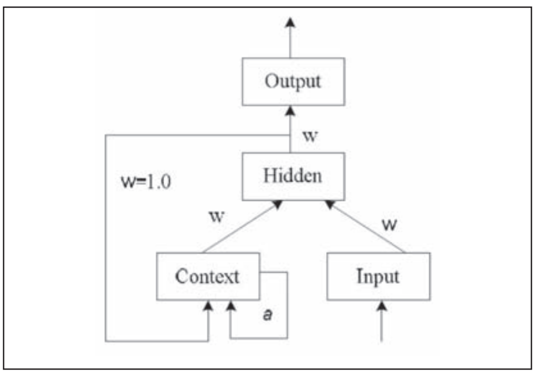

Fig. 1 : The structure of the ENN

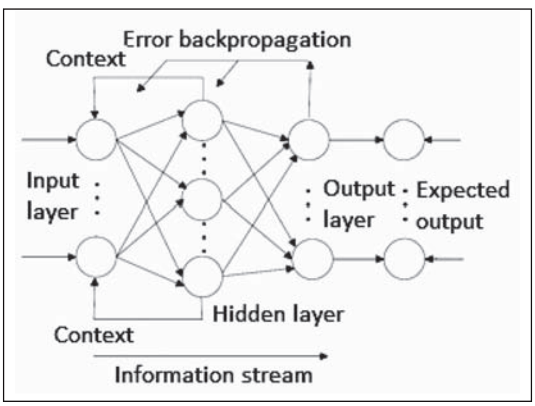

Fig. 2 : Internal process analysis of ENN

context units that are to be used when the network is operated next time. The recurrent context provides a weighted sum of the previous values of the hidden units as input to the next hidden units. The activations are copied from hidden layer to context layer on a one for one basis, with fixed weight of 1.0 (w= 1.0). The forward connection weight is trained between hidden units and context units as well as other weights and self-connections are introduced to the context units when the values of the self connection weights (a) are fixed between 0.0 and 1.0 before the training process (ZhiQiang *et al.,* 2007). In the internal learning process of ENN, we can see the error back-propagation algorithm, as training such a network is not straightforward since the output of the network depends on the inputs and also all previous inputs to the network (Fig. 2).

Training and testing the data

For the above ENN model, the input layer nodes *viz*., weather parameters (rainfall, temperature -minimum, maximum and mean) along with productivity and year class were incorporated in Levenberg-Marquardt back-propagation algorithm and the network structure was 12-7-1 and 6-2-1 (Table 2). The applied transfer functions for the above ENN model are linear, log-sigmoid and hyperbolic tangent sigmoid. Mapping for the hidden layer nodes and transfer functions was carried out based on trial and error method, as there is no standard methodology for selecting the same. The data set used in this study was normalized for the input layer. The efficiency/response of the neural network for accurate output was measured using statistical indices *viz*., root mean square error (*RMSE*), regression coefficient (R^2) as per standard procedures (Sreekanth *et al*., 2009).

RESULTS AND DISCUSSION

In the present study the historic data sets (1990-2010) of weather variables along with production and productivity of major oil seed crops in Andhra Pradesh *viz.,* groundnut, sunflower, sesame, castor and safflower were used to understand the regional climate change impacts.

Descriptive statistics of weather variables

The statistical analysis was carried out to understand the trend (increase or decrease), of weather variables *viz*., max. & min. temperatures and rainfall over last two decades (1990-2010). The max temp exhibited positive trend when considered northern Andhra Pradesh and showed an increase by 0.30°C over the last 20 years accounting for 0.89% change. Similarly the min temp also showed upward trend with an increase by 0.05°C over the last 20 years accounting for 0.24% change. The rainfall also surged up to 20.78 mm accounting for 2.48% change in northern AP. In case of southern AP,

Table 1 : Correlation analysis of climate variables along with crop production parameters

Variables	Correlation coefficients (*r*)					
	Mean temp.	**Max. temp.**	**Min. temp**	**Rainfall**	**Oil seeds production**	**Oil seeds productivity**
I. State as whole						
Year class	0.13*	0.17*	0.24*	---	0.15*	---
Oil seeds Production	0.17*	0.24*	---	---	---	---
Oil seeds Productivity	0.18*	0.15*	0.16*	0.14*	---	---
Rainfall	0.15*	---	0.18*	---	---	---
Max. temp.	---	---	0.57**	---	---	---
II . Crop wise						
Sesame	0.29*	0.19*	0.26*	---	---	---
Sunflower	0.18*	0.15*	0.15*	---	---	---
Groundnut	0.41*	0.41*	0.25*	0.32*	---	---
Safflower	---	0.20*	---	0.27*	---	---
Castor	---	---	---	---	---	---

*Significant at P=0.05%; ** Significant at P=0.01%

0.71% change in max temp with an increase of 0.24°C, 1.21% increase in min temp with an increase of 0.28°C and 7.65% change in rainfall received amounting to 59.30 mm was observed. In northern AP, kurtosis ranged from -2.15 to +2.29 for max temp, -2.65 to +2.64 for min temp and +0.15 to +2.49 for rainfall. In southern AP, kurtosis ranged from -2.21 to -0.72 for max temp, +2.50 to +5.01 for min temp and from -1.79 to +2.65 for rainfall. Kurtosis, the measure of "peakedness" of the probability distribution of a real-valued random variable was always <3.0 for all the weather variables viz., rainfall, min temp and max temp in northern AP thereby explaining more of the variance to be due to frequent modestly-sized deviations rather than infrequent extreme deviations in the weather variables under study. In other terms it explains the platykurtic distribution with values spread wider around the mean. In southern AP, it exhibited similar trends for max temp and rainfall. However, the kurtosis for the min temp was >3.0 during the majority of the years explaining leptokurtic distribution with more values concentrated around the mean explaining high probability for extreme deviations.

State as a whole

There is no direct measurement to understand the long term variation in climate variables. However, correlation analysis was used to measure the relationships between different variables under study for two decades (1990-2010). The year-class exhibited a significant positive correlation with different variables *viz.,* mean temp, max temp, productivity and production. The oilseed production exhibited a significant positive correlation with mean temp, max temp; oilseed productivity exhibited a significant positive correlation with rainfall, mean temp, max temp, min temp; rainfall exhibited a significant positive correlation with mean temp, min temp; max temp also exhibited a highly significant positive correlation with min temp (Table 1).

Prediction of climate change effects on oilseed crops

Similar to weather data analysis, crop-wise correlation analysis also yielded a few significant relationships. The crops *viz.,* sesame (with mean temp, min temp, max temp), sunflower (with mean temp, min temp, max temp); groundnut (with rainfall, mean temp, min temp, max temp); safflower (with rainfall, max temp) in particular also exhibited a significant positive correlation with temperature and rainfall variables (Table 1). Castor did not exhibit any significant relationship, however, and the trend was found to be negative with temperature and rainfall variables.

Prediction of sunflower productivity in the state as a whole based on weather variables explained the variability in the sunflower productivity to the tune of 10%. The best fit relationship for predicting sunflower productivity with a reliability of 50% was obtained with ENN model. In case of castor, the traditional regression analysis could predict the productivity to the tune of 23%. The ENN model could enhance the reliability of prediction to the tune of 54%. The productivity of ground nut can be predicted with an accuracy of 34%. Whereas, the enhanced R^2 value (0.66) was observed through ENN modeling. The variability in sesame

Table 2 : ANN model for Crop-wise and its performance

Response variable	Predictor variables	Node structure	Transfer functions*	Epochs	Processing time	R^2	RMSE
Groundnut	Max.Temp, Min.Temp, Mean Temp, RF and Year	12-7-1	Radial basis, Hyperbolic tangent sigmoid, Linear (Purelin)	500	54.84	0.66	0.82
Castor	-do-	-do-	-do-	46	7.9	0.54	0.24
Sesamum	-do-	-do-	Linear (Purelin), Log-sigmoid, Hyperbolic tangent sigmoid	500	84.69	0.69	0.16
Safflower	-do-	-do-	-do-	80	13.36	0.75	0.24
Sunflower	-do-	-do-	Hyperbolic tangent sigmoid, Log-sigmoid, Linear (Purelin)	1000	163	0.50	0.65
Max.Temp	Year	6-2-1	Log-sigmoid, Hyperbolic tangent sigmoid, Hyperbolic tangent sigmoid	6	1.36	0.99	1.05
Min.Temp	Year	6-2-1	Log-sigmoid, Hyperbolic tangent sigmoid, Radial basis	3	0.88	0.92	5.93

*Algorithm used Levenberg-Marquardt back propagation with Elman network

productivity that can be predicted through traditional regression is 11%. The ENN model could predict the sesame productivity up to the tune of 69% with enhanced accuracy over traditional regression models. The productivity of safflower through regression analysis was explained to the tune of 11%. The ENN model enhanced the prediction accuracy up to 75% (Table 2).

On the whole the ENN models performed better over traditional regression models in predicting the yield responses across all the crops (Fig. 3).

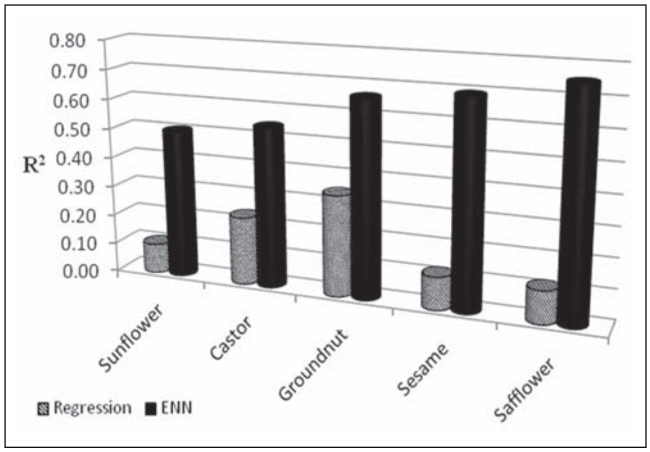

Fig. 3 : Comparison of crop-wise predictive performance of Regression and ENN models

Region-wise analysis

The region wise correlation analysis trend followed the similar trend exhibited by the state as a whole but for minimal deviations. The mean and max temperatures for both south AP and north AP showed distinct upward trend, though northern AP experienced quite higher max temperatures compared to southern AP. The variability in the max temp trend in the southern AP due to year class was explained to the tune of 11% through linear function and to the tune of 30% through polynomial order (6). Similarly, for northern AP the variability in the max temp trend was explained up to 34% through linear function and 59% through polynomial order (6) function (Table 3).

Unlike, max mean temperature, in case of min mean temperature, the northern AP exhibited comparatively lower range than southern AP. The regression analysis could explain the variability in min temp to the tune of 2-22% through linear and polynomial functions respectively. Similarly, for southern AP, the variability in min mean temp explained due to year class was ranged from 15-27% through linear and

Table 3 : Influence of abiotic variables on oilseeds production a) Crop-wise regression models b) Region-wise regression models

Response variable	Predictor variables	Regression model	R^2	Significance
a) Crop wise regression models				
Groundnut	1-5*	$y = -56.41 + 0.001_{RF} - 5.60_{Mean\ temp} + 2.94_{Min.\ temp} + 2.95_{Max.\ temp} + 0.02_{YC}$	0.34	F=34.21; P< 0.0001; df=334
Castor	-do-	$y = -2721.28 + 0.001_{RF} - 211.91_{Mean\ temp} + 106.17_{Min.\ temp} + 100.58_{Max.\ temp} + 1.47_{YC}$	0.23	F=8.44; P<0.0001; df=144
Sesamum	-do-	$y = -738.33 + 0.001_{RF} - 105.52_{Mean\ temp} - 49.95_{Min.\ temp} - 50.61_{Max.\ temp} + 0.32_{YC}$	0.11	F=6.82; P< 0.0001; df=274
Safflower	-do-	$y = -61.94 + 0.02_{RF} + 665.52_{Mean\ temp} - 336.45_{Min.\ temp} - 325.33_{Max.\ temp} - 0.04_{YC}$	0.11	F=2.51; P=0.04; df=98
Sunflower	-do-	$y = -2526.58 + 0.02_{RF} - 520.22_{Mean\ temp} + 262.98_{Min.\ temp} + 263.21_{Max.\ temp} + 1.21_{YC}$	0.10	F=5.171, P= 0.0001, df = 232
b) Region wise regression models				
Max. Temp	5	$y = -0.44 + 0.02_{YC}$ (SAP)#	0.11	F=2.32; P = 0.1, df = 17
		$y = -18.99 + 0.03_{YC}$ (NAP) ##	0.34	F=8.87; P = 0.01, df=17
Min. Temp	-do-	$y = 5.17 + 0.72_{YC}$ (SAP)	0.58	F= 25.25; P <0.001; df = 18
		$y = 8.72 + 0.01_{YC}$ (NAP)	0.02	F= 0.45; P = 0.5; df =18
Rainfall	-do-	$y = 21.65 + 0.0003_{YC}$ (SAP)	0.01	F= 0.30; P = 0.5; df = 18
		$y = 8.72 + 0.01_{YC}$ (NAP)	0.02	F= 0.45; P = 0.5; df = 18

*1= Max. temp., 2= Min. temp., 3=Mean temp., 4=rainfall (RF), 5= year class (YC); #=Southern AP(SAP); ## =Northern AP (NAP)

polynomial functions respectively. Here also, the mean min temperatures showed upward trend like max temperature (Table 3).

With respect to rainfall no clear pattern was observed between the regions. However, the variability in the rainfall pattern over years was explained to the tune of 2-40% through linear and polynomial order 6 in case of northern AP and to the tune of 2-47% in case of southern AP respectively due to linear and polynomial order (6) (Table 3).

The ANN analysis with node structure of 6-2-1 could predict the min and max temperatures of AP to the tune of 0.92 and 0.99 respectively (R^2 values) and $RMSE$ is 5.93 and 1.05 respectively.

Realized change in the oilseed productivity and weather variables

The calculated realized district-wise change for both productivity and weather variables are presented in Fig. 4. In case of safflower, the change in productivity ranged from -48.79 (KUR) to +90.74 (RR). The corresponding realized change in rainfall ranged from -7.12% (ADB) to +20.32% (ATP); from +0.04 (NZB) to +1.78 (ADB) in case of min temp and +0.59% (RR) to +0.82 (MNR) in case of max temp. Usually safflower adapted to wide range of climatic conditions and the crop is tolerant to low temperature (<15°C) at seedling and vegetative stages but sensitive at elongation, flowering and post flowering stages. It usually comes up well in relatively drier areas. Sunflower is highly sensitive to high soil temperature and thrives well in warm dry climates with 26-30°C. The temperatures >38°C are detrimental to the crop. For sunflower, the realized change in productivity, rainfall, min. Temp and max. Temp ranged from -35.33% (ATP) to +110.1% (KRN); -9.15% (ADB) to 35.37% (CDP); -0.01% (KRN) to +1.55% (ADB); +0.16% (CTR) to +0.80% (ATP) respectively.

For castor, the change in productivity, rainfall, min and max. Temperatures ranged from +17.30% (NLD) to +130.69 (PKS); -8.60% (ADB) to +18.44% (ATP); +0.30% (KRN) to +1.79% (ATP) and +0.28% (ADB) to 0.84 (PKS) respectively. For groundnut, the realized increase or decrease in productivity, rainfall, min and max temperatures ranged from -40.72% (ATP) to +112.86% (MNR); -8.60% (ADB) to +18.51% (ATP); +0.04% (KRN) to +1.49% (ATP); +0.16% (CTR) to +0.84% (PKS) respectively. Usually, for groundnut temperature is a major environmental factor that determines the rate of crop development. Temperatures >35°C inhibit the growth of crop. The crop mean optimum temperature is around 30°C and at <15°C growth ceases.

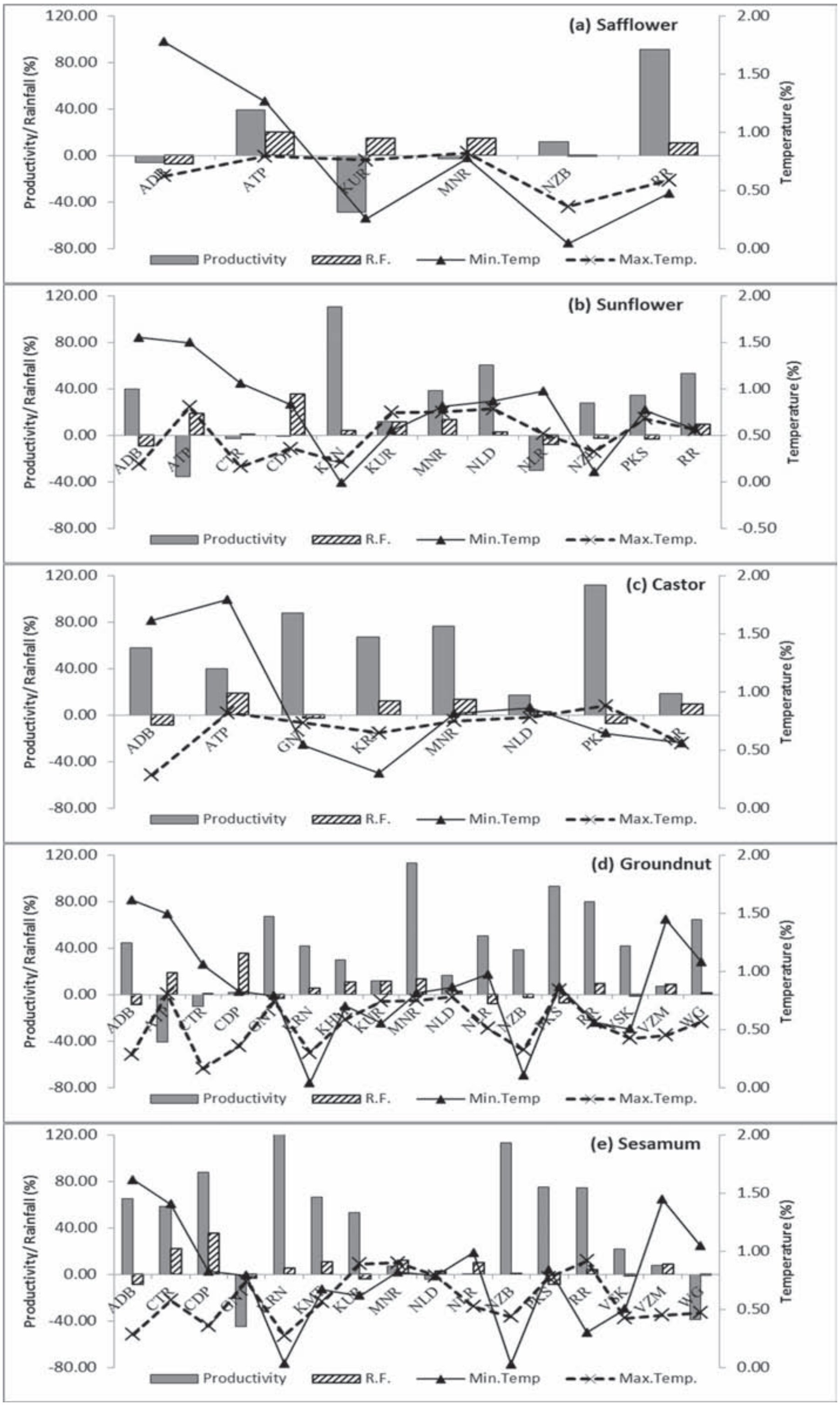

Fig. 4 : The realized change in the productivity and weather variables of 1990-95 over 2005-10 in major oil seed crops

For sesame, the change in productivity, rainfall, min and max temperatures ranged from -9.15% (WG) to +113.04 (NZB); -8.61% (PKS) to +21.26% (CTR); -0.15% (KRN) to +1.61% (ADB) and +0.28% (ADB) to +0.92% (RR) respectively. Sesame needs a constant high temperature of about 26-30°C with min temperature around 12°C. Therefore usually the crop is grown during cooler seasons in warmer regions and as a summer crop in cooler regions. The pollination and formation of capsules is inhibited during heat wave period (>40°C).

Overall, the oilseed productivity showed a positive trend with increased temperatures except for minor deviations observed for particular crops. However, the present study considered only limited direct climate variables leaving behind several other interrelated variables such as solar radiation, CO_2/ ozone levels, critical stages of crop etc that are crucial in deciding the yield potential of oil seed crops. Researchers at the University of Antwerp have suggested that the increased ozone levels as a result of climate change could affect crops in various European regions differently than previously expected. Further they mentioned that higher levels of ozone affect not only the yield, but also the percentage of oil content. The project's coordinator, Karine Vandermeiren, expressed that: *"If the predictions of the global panel on climate change are correct, we could be looking at a 10 to 15 per cent reduction in yield by 2100. If you combine that with oilseed productivity loss it's even more…Combined, these two aspects would be serious for farmers."*

CONCLUSIONS

In the present study, the predicted changes of climate on oilseed crops varied greatly by crop and region and further detailed studies are to be envisaged to improve the accuracy levels of prediction considering several other interrelated variables which are otherwise missing in the present study. Specific variables such as changes in temperature, CO_2 levels, precipitation, and solar radiation and their interaction effects should used to model the climate change more precisely as these variables can both increase and decrease crop yields with changes in climate. Further, climate change may also predicted to lead to crop boundary changes for certain crops, mapping such boundary expansions/ restrictions through latest geospatial tools will enhance sensitivity and relevance of climate change studies for oil seeds in future.

REFERENCES

Elman, J.L. (1990). Finding Structure in Time, *Cognitive Sci*., 14:179-211

Gail, M., Brion, T.R., Neelakantan and Srinivasa Lingireddy. (2002). A neural-network-based classification scheme for sorting sources and ages of fecal contamination in water. *Water Res*., 36: 3765–3774

Guan, P., Huang, D and Zhou, B. (2004). Forecasting model for the incidence of hepatitis A based on artificial neural network. *World J Gastroenterol*., 10(24): 3579–3582

Hegde, D.M. (2007). An overview of oilseed scenario in India and scope and potential of bio-fuel crops. Paper presented in the Expert Group Discussion on Role of Bio-fuels for Decentralized Application in Agriculture and Allied Activities, May 14-15, 2007 at Administrative Staff College of India, Hyderabad.

Heyi Wang and Yi Gao. (2011). Elman's Recurrent Neural Network Applied to Forecasting the Quality Of Water Diversion in the Water Source Of Lake Taihu, International Conference on biology, Environmental and chemistry. Vol.1. pp. 283-28

Mendham, N.J., Shipway, P.A and Scott R.K. (1981). The effect of delayed sowing and weather on growth, development and yield of winter oil-seed rape (*Brassica napus*). *J Agri Sci*., 96:389-416

Morrison, M.J., Mc Vetty, P.B.E and Shaykewich, C.F. (1989). The determination and verification of a basaline temperature for the growth of westar summer rape. *Canadian J Plant Sci*., 69(2): 455-464

Sidlauskas, G and S Bernotas. (2003). Some factors affecting seed yield of spring oilseed rape (*Brassica napus* L.). *Agronomy Res.*, 1(2): 229-243.

Sreekanth, P. D., Geethanjali, N., Sreedevi, P. D., Shakeel Ahmed, Ravi Kumar N and Kamala Jayanthi, P. D. (2009). Forecasting Groundwater level Using Artificial Neural Networks. *Curr Sci*., 96(7): 933-939

Thurling, N and Vijendra Das, L.D. (1977). Variation in the pre-anthesis development of spring rape (*Brassica napus* L.). *Australian J Agri Res*., 28(4): 597-607

ZhiQiang Zhang, Zheng Tang and Catherine Vairappan. (2007). A Novel learning method for elman neural network using local search, Neural Information Processing letters and reviews., 11(8): 181-188