



Sensitivity of evapotranspiration to climate change using DSSAT model in sub humid climate region of Eastern Uttar Pradesh

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Abstract

Climate variability impacts the components of hydrological cycle especially evapotranspiration (ET) and soil moisture, that plays a crucial role in determining water flux of an agriculture system and is thus, essential to study the response of ET to climate change. The present study is an attempt to understand the trend in observed ET (1978–2003) and variation in projected ET RegCM4.0, RCP 4.5 scenario during 2040–2060. Observed ET is compared with simulated ET using NCEP, NASA Power, RegCM4.0 and agriculture field data. Apart from studying the effect of relative humidity (RH), solar radiation (SLR), minimum and maximum temperature and wind speed (WS) on ET, the FAO Penman–Monteith and Priestly–Taylor methods in CERES Rice and CERES Wheat crop model were used to simulate ET. Further, the cumulative impact of rainfall and ET on agriculture drought has been estimated based on standardized Reconnaissance Drought Index (RDIst). The result shows a declining trend of ET during 1978–2003, but an increase during 2040s (2040–2061) for both wheat and rice. Overall, the ET simulated using weather data input from agriculture field shows highest concordance with observed ET, followed by NASA/RegCM4 and NCEP. Moreover, the FAO Penman–Monteith gives more accurate result in comparison to the Priestley–Taylor method. Environmental modification suggests that RH is the most influential parameter for ET followed by temperature, SLR and WS. Based on RDIst it was observed that rainfall is negatively associated with ET and their cumulative effect on water availability can be efficiently estimated using drought index.

Keywords CERES-wheat · CERES-rice evapotranspiration · FAO Penman–Monteith · Priestley–Taylor · Reconnaissance Drought Index

Introduction

One of the most important issues raised by climate change is to ensure water and food security for the ever increasing population while sustaining the already stressed environment (Aggarwal and Mall 2002; Lal et al. 2005; Mishra et al. 2013; Mall et al. 2017). Sufficient water availability and minimum water loss are crucial for crop productivity. Global climate change is likely to alter the magnitude and distribution of evapotranspiration, streamflow, and plant-available soil water (Federer et al. 1996; Mall and Gupta 2000, 2002; Irmak et al. 2012; Gao et al. 2017). Evapotranspiration (ET)

being one of the major components of the hydrological cycle is thus an important factor for agricultural yield. “ET represent the dominant loss of water from catchment worldwide, with over 62% of global land-surface precipitation accounted for by ET” (Mall et al. 2002; Sing et al. 2010; Guo et al. 2017).

ET is affected by various factors such as—soil moisture, plant type, plant development stage, changes in the distribution of moisture and energy in the atmosphere. All these factors are associated with change and thus ET is majorly dependent on climate variability (Milly and Dunne 2016; Banerjee et al. 2016; Kundu et al. 2017; Gao et al. 2017; Lei et al. 2018). “Evapotranspiration increases with increasing temperature, increasing radiation, decreasing humidity, and increasing wind speed (Abteu and Melesse 2013). ET can be estimated using different methods namely Thornthwaite method (Thornthwaite 1948), Blaney Criddle method (Blaney and Criddle 1950), Priestley Taylor method (Priestly and Taylor 1972),

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Hargreaves method (Hargreaves and Samani 1985) and FAO Penman–Monteith method (Doorenbos and Pruitt 1975). Each of these methods follows a standard equation for ET estimation on the basis of certain weather parameters. Espadafor et al. (2011) and Shweta and Krishna (2015) observed that FAO Penman–Monteith gives more accurate results when reliable wind speed, solar radiation, vapor pressure data is available. In case of limited availability of climate data ET estimation method based on temperature and radiation show better results (Sentelhas et al. 2010; Grace and Quick 2013; Babatunde et al. 2017).

Since 1990, crop simulation model such as DSSAT and Infocrop has become an important tool in the estimation of crop yield and evapotranspiration owing to its advantage in simulating the interactions between genotype, environment and management (Bai and Tao 2017). Other models such as CropWat, SWAT, EPIC and Aqua crop model are also used to simulate crop yield response to water availability (Pawar et al. 2017). DSSAT is a crop simulation model that can be beneficial for impact assessment of climate change on crop yield and is of much use for farm recommendation and policymakers (Jones et al. 2003). DSSAT is used to simulate ET, crop development and wheat and rice yield using CERES module (White et al. 2011) and also in impact studies of ET (Lv et al. 2017; Shrivastava et al. 2018).

Moreover, ET has been an important parameter in estimating agriculture drought, a condition of water stress where sufficient water is not available for crop growth. It has a great impact on crop production. Therefore, regular drought monitoring is required for impact reduction and food security. Zhao et al. 2017 proposed agriculture drought index based on drought rarity and ET. It analyses the response of agriculture drought to meteorological drought. Various researchers have calculated drought index using precipitation and ET to study the impact of agriculture drought on crop productivity (Tasakiris and Vangelis 2005; Madhu et al. 2015; Prabnakorn et al. 2018).

In view of above preamble, present study aims to: (1) analyze long-term trend of ET for rice and wheat over Varanasi region for the period of (1978–2003) and future change in ET (2040–2060), (2) comparison of observed ET (measured using Lysimeter) to ET simulated using weather station data, NASA power, RCM and NCEP data through CERES Wheat and CERES Rice crop model, (3) estimating the response of ET to change in climate variable such as temperature, solar radiation, wind speed, relative humidity through environmental modification in the DSSAT model, (4) calculate reconnaissance drought index by cumulative impact of rainfall and ET on aridity in Varanasi.

Materials and method

Study site

The present study is based on Varanasi, a region in Eastern Plain Zone of Uttar Pradesh (Fig. 1). Varanasi is situated at an elevation of 80.71 m amsl having a latitude of 25°18'N and longitude of 83°01'E in a subtropical climate with a population of 3.6 million (Singh et al. 2018).

Data used

In this study daily meteorological data of maximum and minimum temperature, solar radiation, wind speed and relative humidity over a period of 1978–2003 were obtained from the India Meteorological Department (IMD), New Delhi, NASA power (1° × 1° resolution), NCEP (0.38° × 0.38° resolution), and agriculture department, BHU. Observed evapotranspiration data measured using lysimeter was taken from IMD, New Delhi. The RCM (RegCM4) data was obtained from CCCR- IITM (LMDZ; RCP 4.5 scenario) for 2040s (2040–2060) developed by National Center for Atmospheric Research (NCAR), ICTP—Italy in 2010 (Giorgi 2012). Quantile mapping approach was used for bias correction of RCM data. In this process biasness was removed by fitting a cumulative probability distribution (CDF) $F_{\text{obs}}(x_{\text{obs}})$ to the observed data, similarly, another distribution $F_{\text{grid-c}}(x_{\text{grid-c}})$ is fitted to the RCM data in a grid. The grid value matching to the probability distribution of the observation has been done to obtain the “bias-corrected” grid data ($x_{\text{grid-c}}$) for the current climate as below (Qian et al. 2016).

$$Z_{\text{model-present-corrected}} = F_{\text{obs}}^{-1}(F_{\text{model-present}}(Z_{\text{model-present}})).$$

Using the equidistant CDF matching method, it was assumed that the difference between the model and observed values during the current climate would also be applicable for the future climate; therefore, the bias-corrected RCM data for the future $x_{\text{grid-f-corrected}}$ can be obtained as:

$$Z_{\text{future model-corrected}} = Z_{\text{future model}} + F_{\text{obs}}^{-1}(F_{\text{future-model}}(Z_{\text{future-model}})) - F_{\text{model}}^{-1}(f_{\text{future-model}}(X_{\text{future-model}}))$$

where $F_{\text{future-model}}(Z_{\text{future-model}})$ is the CDF of the RCM data $Z_{\text{future-model}}$ at the grid data (Qian et al. 2016).

Decision support system for agrotechnology transfer (DSSAT) model

Its main aim is to provide crop simulation modeling output for better agronomic research. It integrates information about

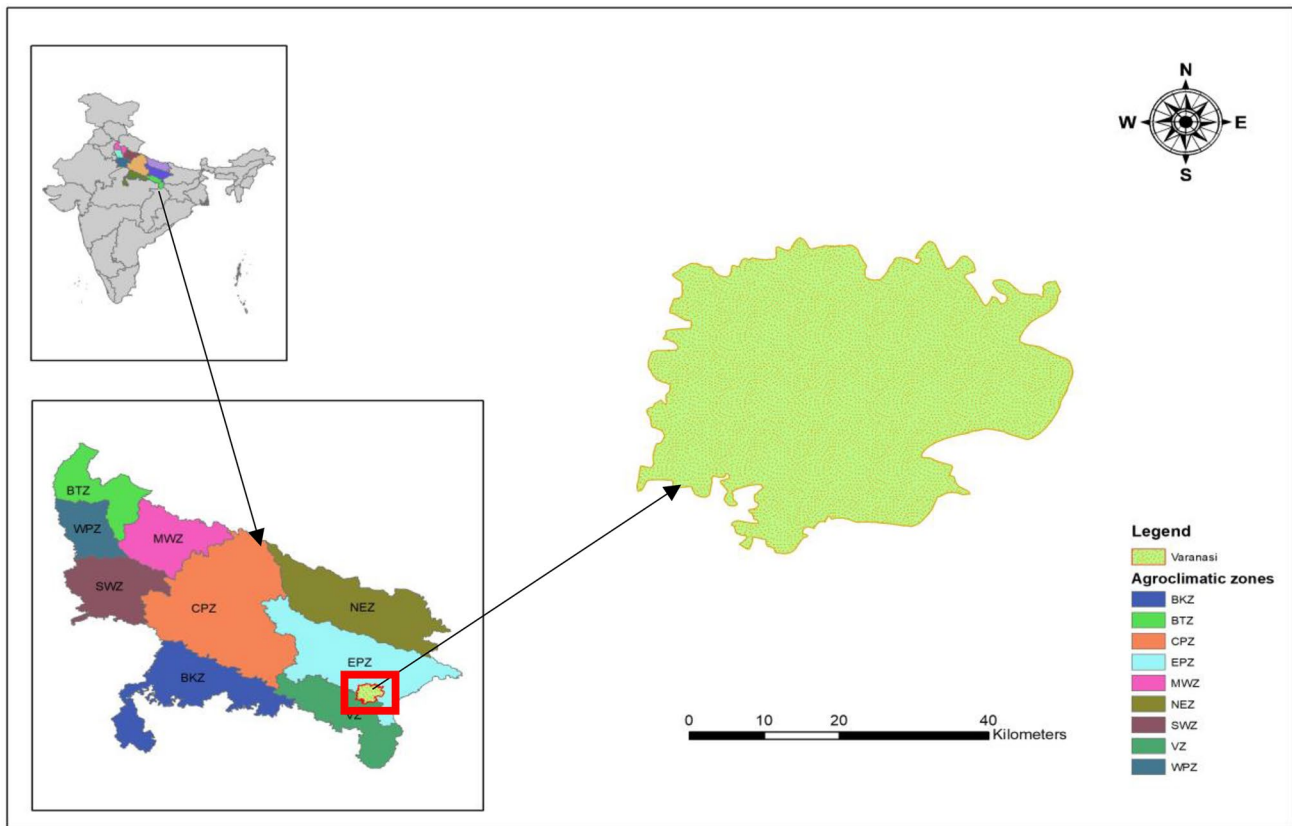


Fig. 1 Location map showing study site (Varanasi)

soil, weather, crop, and agriculture management techniques of different crops together for better decision making (Jones et al. 2003; Mall et al. 2016). CERES module of DSSAT is a plant growth module that simulates the growth of individual crop species. It uses a set of code for simulation of evapotranspiration, soil water balance and plant nitrogen (White et al. 2011). In the present study, CERES-Rice and CERES-Wheat model was used for evapotranspiration simulations. The DSSAT model provides potential ET value based on the Priestley–Taylor and Penman Monteith equation, using this it calculates actual soil water Evaporation and transpiration for further estimation of actual ET (Shelia et al. 2018). The calibrated and validated CERES-Wheat and CERES-Rice crop model (Mall and Aggarwal 2002; Singh et al. 2016; Mall et al. 2017) for different cultivars such as HUU-234 for wheat and MALVIYA-36 for rice has been used for simulating evapotranspiration over the study period (1978–2003).

ET estimation method

ET was estimated using Priestly–Taylor method and FAO Penman–Monteith method as given below $\left\{ \frac{S}{S+Y} \right\}$.

1. Priestly and Taylor method (1972)

It is based on net radiation energy (Q^*) which is a driving factor for ET especially in well-watered condition. Besides, a temperature dependent weight factor and a constant (a) derived by local calibration is also used for ET estimation (Priestly and Taylor 1972):

$$PE = a \left\{ \frac{S}{S+Y} \right\} Q^*$$

2. Penman Method (1963)

It is focused on mass and energy balance, surface and aerodynamic resistance. ET estimation through Penman method requires net radiation, wind, temperature and humidity inputs (Doorenbos and Pruitt 1975)

$$PE = S/(S+Y) \{ Q^* + f(u)(e_a^* - ea) \}$$

where, S is the slope of the saturation vapor pressure–temperature curve, Y is the psychrometric constant, e_a^* is saturated vapor pressure of the air (mb), Q^* is net radiation (cal/cm^2) and $f(u)$ is a wind function (Doorenbos and Pruitt 1975).

Trend analysis

Mann Kendall trend test is a non-parametric test commonly used for observing significant trends in time series. It is based on the rank of observation instead of real values. This reduces the impact of outliers (Kumar et al. 2016). Mann Kendall test has been used in various hydrological and climatological studies to detect the significance of long-term trends (Hamed 2008; Xu et al. 2010; Taxak et al. 2014; Kumar et al. 2016).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i)$$

where n represents number of years, x_i and x_j represent annual values of ET in i and j years respectively (Mann 1945; Kendall 1975).

$$\text{sgn}(x_j - x_i) = \begin{cases} 1, & x_j < x_i \\ 0, & x_j = x_i \\ -1, & x_j > x_i \end{cases}$$

For $n \geq 10$, S is normally distributed with mean = 0 and Variance as:

$$\text{VAR}(S) = 1/18[n(n-1)(2n+5) - \sum_{k=1}^j tk(tk-1)(2tk+5)]$$

Here j is the number of tied groupss (equal values) and tk is number values in k group (Kumar et al. 2016).

$$Z = \begin{cases} S - 1/\sqrt{\text{VAR}(S)} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ S + 1/\sqrt{\text{VAR}(S)} & \text{if } S < 0 \end{cases}$$

Z test is used for trend analysis, Null hypothesis if true represent no trend (H_0 = no trend), Alternate Hypothesis if true represents presence of trend (H_1 = significant trend) (Kumar et al. 2016). The null hypothesis is rejected if $Z > Z_{1-\alpha/2}$. In this study, performance is calculated at 5% significance level.

Sensitivity analysis

The response of ET to an elevated temperature, solar radiation, wind speed, relative humidity and CO₂ concentration due to climate change was seen as a part of sensitivity analysis. Firstly, the individual impact of these climate variables on ET was observed. All the factors were modified in the range (5–20%) from the average value using the DSSAT

environmental modification component. Thus, 20 different treatments were applied to study the impact of individual climate variable on ET. Secondly, using permutation and combination- 15 different treatments were applied to study the combined effect of all the variables on evapotranspiration (ET). Percentage change in simulated ET owing to environmental modification was recorded.

Drought Index

The annual rainfall and evapotranspiration data (1978–2003) is used for estimation of reconnaissance drought index (RDI_{st}) (Madhu et al. 2015). RDI is used for the analysis of agricultural drought based on the cumulative effect of rainfall and ET. It helps in analyzing the response of agricultural drought to meteorological drought.

$$\text{Formula used: } ak = \left(\frac{\sum_{j=1}^{j=k} P_j}{\sum_{j=1}^{j=k} ET_j} \right)$$

where P_j and ET_j denote precipitation and ET.

$$\text{RDI}_n(K) = ak / (\text{avg.}ak) - 1$$

where avg.ak is the average value of ak (Madhu et al. 2015).

The standardized RDI is given by

$$\text{RDI}_{st}(K) = \left\{ Y_k - \frac{\text{avg.}Y_k}{k} \right\}$$

where Y_k is the $\ln(ak)$, avg. Y_k is the arithmetic mean and σ_k is standard deviation (Madhu et al. 2015).

Result and discussion

Trend analysis

The non-parametric Man Kendall time series analysis for observed ET shows a declining trend in ET (1978–2003) for rice growing Kharif season (1st July–30th Oct; $p < 0.08$) and wheat growing Rabi season (15th Nov–15th April; $p < 0.001$) as shown in Fig. 2. The projected ET (2040–2060) on the other hand, shows an increase in ET for wheat (186%) and rice (50%) in comparison to 2003. The inverse relationship between ET and rainfall is evident by the work of Meshram et al. 2014 and further supported by Madhu et al. 2015. We found that the years 1979, 1992 that witnessed high ET were declared moderately drought years in Varanasi. Temperature and solar radiation are other important meteorological factors that plays a crucial role in increasing ET through increased vapor pressure that explains the sensitivity of ET towards rainfall, temperature and solar radiation. Thus, the

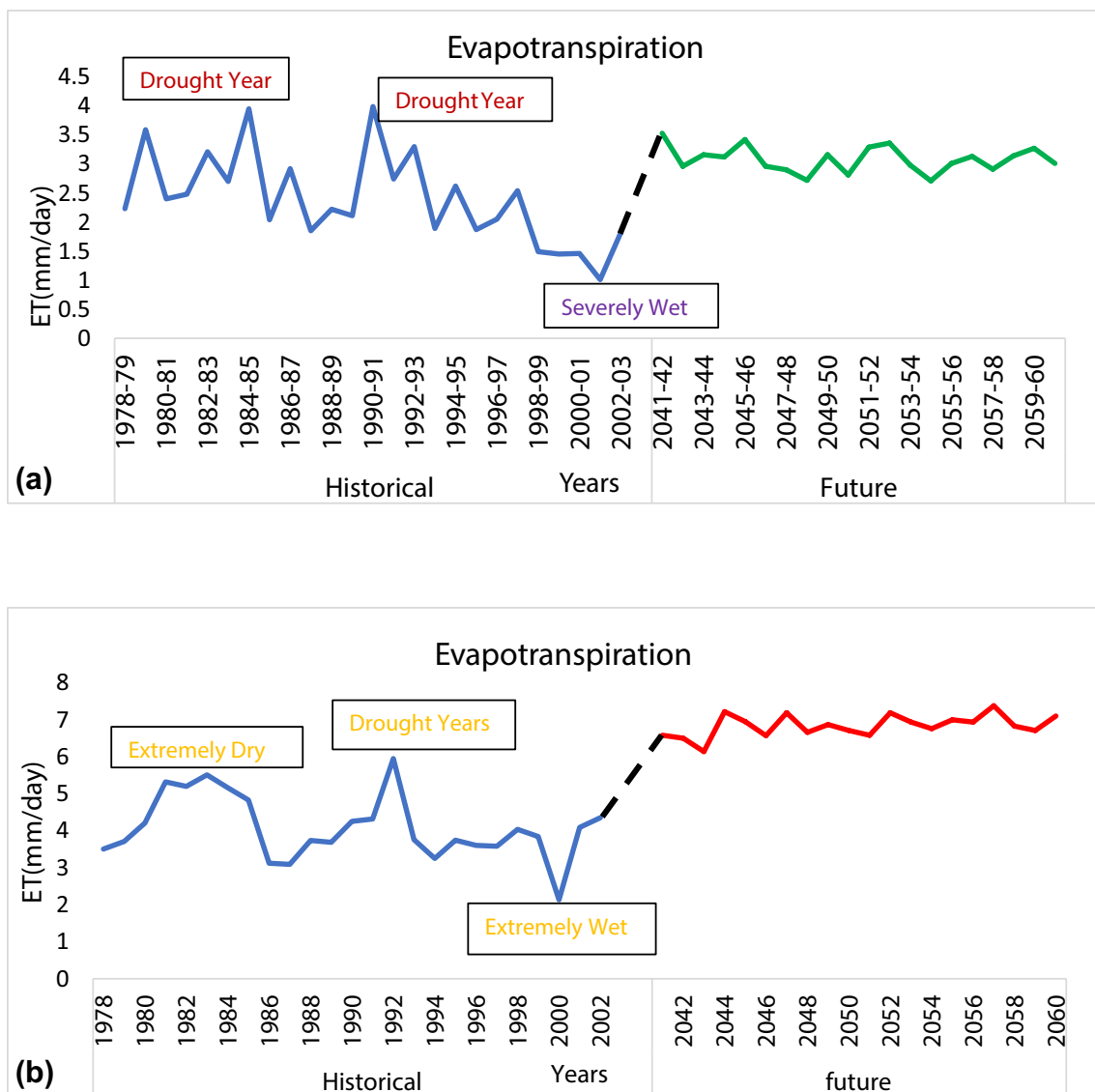


Fig. 2 Historical trend (1978–2003) and future projection (2041–2060) using RCP 4.5 Scenario of evapotranspiration in **a** wheat and **b** rice

projected increase in temperature and rainfall intensity and decline in rainy days will influence ET (IPCC 2013).

Comparison of simulated and observed Evapotranspiration

Simulated ET shows more concordance with actual ET using FAO Penman–Monteith method rather than Priestly–Taylor method. Simulated ET using weather data from agriculture weather station through DSSAT shows a strong positive correlation with the observed ET (wheat

and rice) with comparatively less RMSE of 0.73 and 0.94 for wheat and rice respectively. NCEP data, on the other hand, shows the least correlation in case of Priestly–Taylor while NASA shows the least correlation in FAO Penman–Monteith method. For the pictorial representation of the comparison of observed and simulated ET, Taylor diagram has been used in the present study (Fig. 3). A similar study by (Wang et al. 2017) who compared four different types of Potential evapotranspiration against observed ET found difference in PET estimated using different ET estimation method.

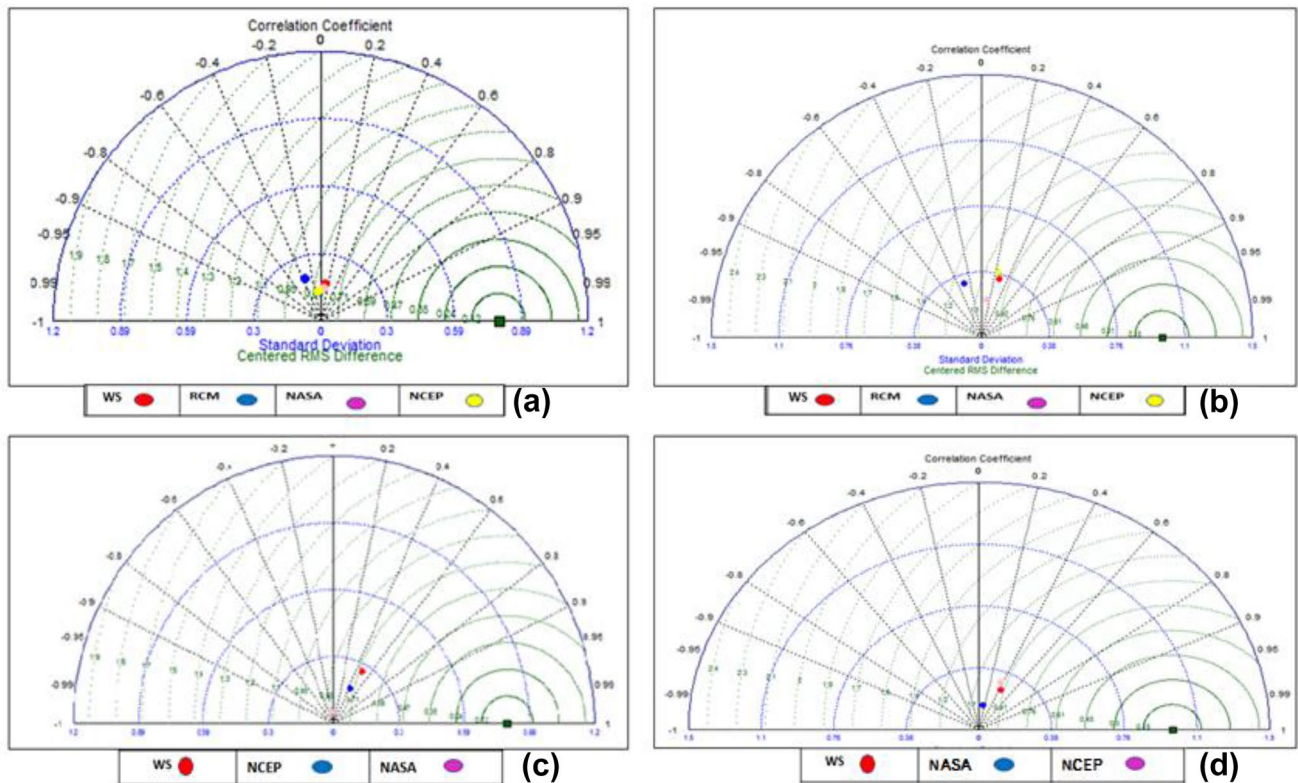


Fig. 3 Taylor Diagram representing correlation coefficient, RMSE and Standard deviation of simulated ET using (priestly Taylor method) in wheat & rice respectively {(a, b) for Priestley Tay-

lor method and (c, d) for FAO penman method [WS Weather station simulated ET, RCM RCM biased corrected data Simulated ET, NASA NASA Power Data Simulated ET, NCEP NCEP Data Simulated ET]}

The results of box plot (Fig. 4) reveal that in case of wheat none of the simulated ET matches the observed using the Priestly–Taylor method but in FAO Penman–Monteith method the ET simulation through weather station data and NASA power is somewhat comparable to the observed but NCEP nowhere falls in the range. Similar is the case in rice except that in case of NASA power using Priestley Taylor method (Table 1).

Sensitivity analysis of evapotranspiration

With the increase in temperature from (1 to 4 °C) there has been an increase in ET in wheat (6–14%) and rice (14–27%). An increase of solar radiation from 0.9 to 3.9 MJ/ m² also lead to increase in ET for wheat (7–24%) and rice (14–28%) both. There is a slight increase in ET for wheat (5–5.5%) and rice (9.3–9.8%) on increasing wind speed from 1 to 4 m/s.

Relative humidity, on the other hand, has a negative impact on ET. Owing to changes in relative humidity from 5 to 20% a decrease from 5 to 60% in wheat and 2 to 59% in rice was noticed. It was observed that ET in rice crop is more sensitive to change in climate variables in comparison to wheat. This might be due to the high evaporation rate in case of kharif than rabi. Temperature and solar radiation are quite high during the July–October period, thus, even a minute variability in these parameters can impact evapotranspiration whereas, in case of winter season evaporation rate and solar radiation is low and comparatively less influenced by variabilities (Fig. 5).

The maximum impact on ET was observed at 10% increase in temperature in combination with 10% increase in solar radiation, wind speed, Relative humidity and CO₂ concentration (Table 2). In case of wheat, ET varied from a marginal increase of 0.41% (combination of 10% increase in temperature and relative humidity) to a drastic increase

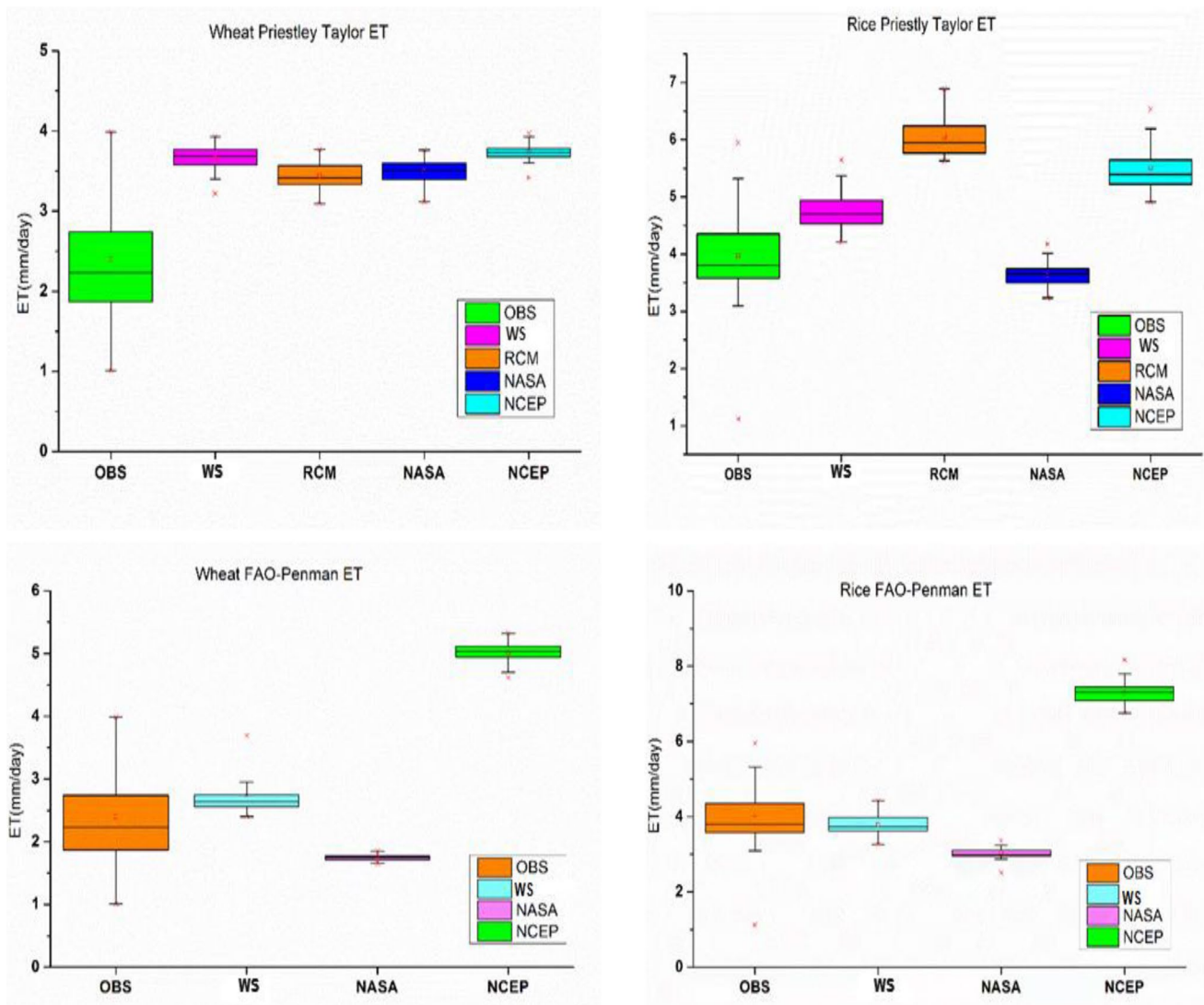


Fig. 4 Box plot representing Evapotranspiration distribution in wheat and rice obtained by using weather input of different sources for Priestley Taylor and fao penman method respectively [WS weather station, RCM RCM biased corrected, NASA NASA Power and NCEP NCEP data]

of 216% (combination of 10% increase in temperature and solar radiation). In case of rice, ET varies in the range 0.32% (combination of 10% increase in temperature and relative humidity/combination of 10% increase in temperature and solar radiation and relative humidity) to 55% (combination of 10% increase in temperature and solar radiation and wind speed or combination of 10% increase in temperature and solar radiation and CO₂ concentration). Priya et al. 2015; Jhajharia et al. 2015; Kundu et al. 2017; Jepsen et al. 2018 have also studied the impact of temperature, rainfall, and CO₂ concentration on ET estimation. It was found that mean temperature influenced the ET most followed by solar

radiation, vapor pressure and wind speed (Priya et al. 2015). Further, it was observed that the effect of temperature is reduced by doubling the concentration of CO₂. Increase in CO₂ might decrease ET as there is reduced stomatal conductance and it might modulate the impact of increased temperature on ET to some extent.

Reconnaissance Drought Index

“Drought index is associated with the cumulative effect of prolonged and abnormal moisture deficiency” (Prabnakorn et al. 2018). Thus, it is strongly connected to agriculture

Table 1 Represent RMSE, correlation coefficient and p value for ET simulated using different weather inputs

Wheat FAO-Penman	RMSE	Correlation coefficient	p value
IMD measured	–	–	
Weather station	0.73	0.517	0.007
NASA	1.01	0.07	0.13
NCEP	2.7	0.38	0.34
Rice FAO-Penman			
IMD measured	–	–	
Weather station	0.94	0.52	0.03
NASA	1.38	0.25	0.54
NCEP	3.44	0.37	0.08
Wheat Priestley			
IMD measured	–	–	
Weather station	1.45	0.12	0.11
NASA	1.34	0.09	0.5
NCEP	1.54	–0.09	0.2
RCM	1.35	–0.34	0.4
Rice Priestley			
IMD measured	–	–	
Weather station	1.09	0.27	0.3
NASA	0.94	0.16	0.9
NCEP	1.69	0.23	0.6
RCM	2.24	–0.3	0.05

water stress. Prabnakorn et al. 2018 observed that standardized precipitation and evapotranspiration index (SPEI) such as Reconnaissance drought index used in this study is more reliable for agriculture drought estimation rather than simply using standardized precipitation index (SPI). The analysis in this study done for drought index estimation as seen in Fig. 6 shows that ET is negatively correlated with precipitation. The dry year with scanty or low rainfall such as 1979, 1992, 1984 have greater loss owing to increased evapotranspiration and can be called as *severely dry years* whereas years with heavy rainfall such as 2001, 2003 witnessed a decrease in evapotranspiration and thus they can be called as *severely wet years*. Furthermore, comparison of historical (1978–2003) and future (2040–2060) drought index suggests that *moderately dry* condition in case of wheat does not exist for future whereas *extremely dry* and *moderately wet* condition is increasing. In case of rice, the *moderately*

wet condition is increasing whereas *near normal* and the *extremely wet* condition is decreasing. The future scenarios for both wheat and rice indicate towards increased agricultural drought. This would have certain negative consequences towards crop yield and will add additional burden to existing food security. Similar studies have been conducted by Tasakiris and Vangelis et al. 2005; Madhu et al. 2015; Prabnakorn et al. (2018) on agriculture drought and aridity based on evapotranspiration and precipitation. This index can be used for projection of drought years in the future based on projected evapotranspiration and precipitation for better estimation of soil moisture deficiency and crop stress.

Conclusion

The seasonal trend of ET for wheat and rice shows a decreasing trend even with the increase in temperature probably due to the decrease in crop duration caused by reduction in solar radiation. Further, there is an increase in relative humidity, rainfall that leads to lower ET. FAO Penman–Monteith gives more accurate results but in case of limited availability of weather parameter, Priestly–Taylor method is preferable. Also, it was observed that although simulated ET using DSSAT is comparable to observed ET, the modeled output underestimates extreme events. Further, in the sensitivity analysis of ET to climate variables, it was observed that relative humidity is the most influential factor followed by temperature, solar radiation and wind speed. Also, ET in case of rice is more sensitive to climate variability than in wheat. The projected ET (RCM 4.5 scenario) is increasing in the case of wheat and rice most probably driven by Increasing temperature, solar radiation and decreased frequency of rainfall in the future. Lastly, the cumulative effect of ET and precipitation to predict agricultural drought, ET shows a negative response to increase in rainfall. The present study suggests that the DSSAT crop model can be used to predict the effect of a change in climate variables on crop evapotranspiration of any region. But, there is a possibility of underestimation of ET when the simulation is based on modeled input data. Since ET plays a crucial role in determining the soil water availability for crop growth, this study can be used for understanding the impact of climate variability on crop water requirement of a sub-humid region.

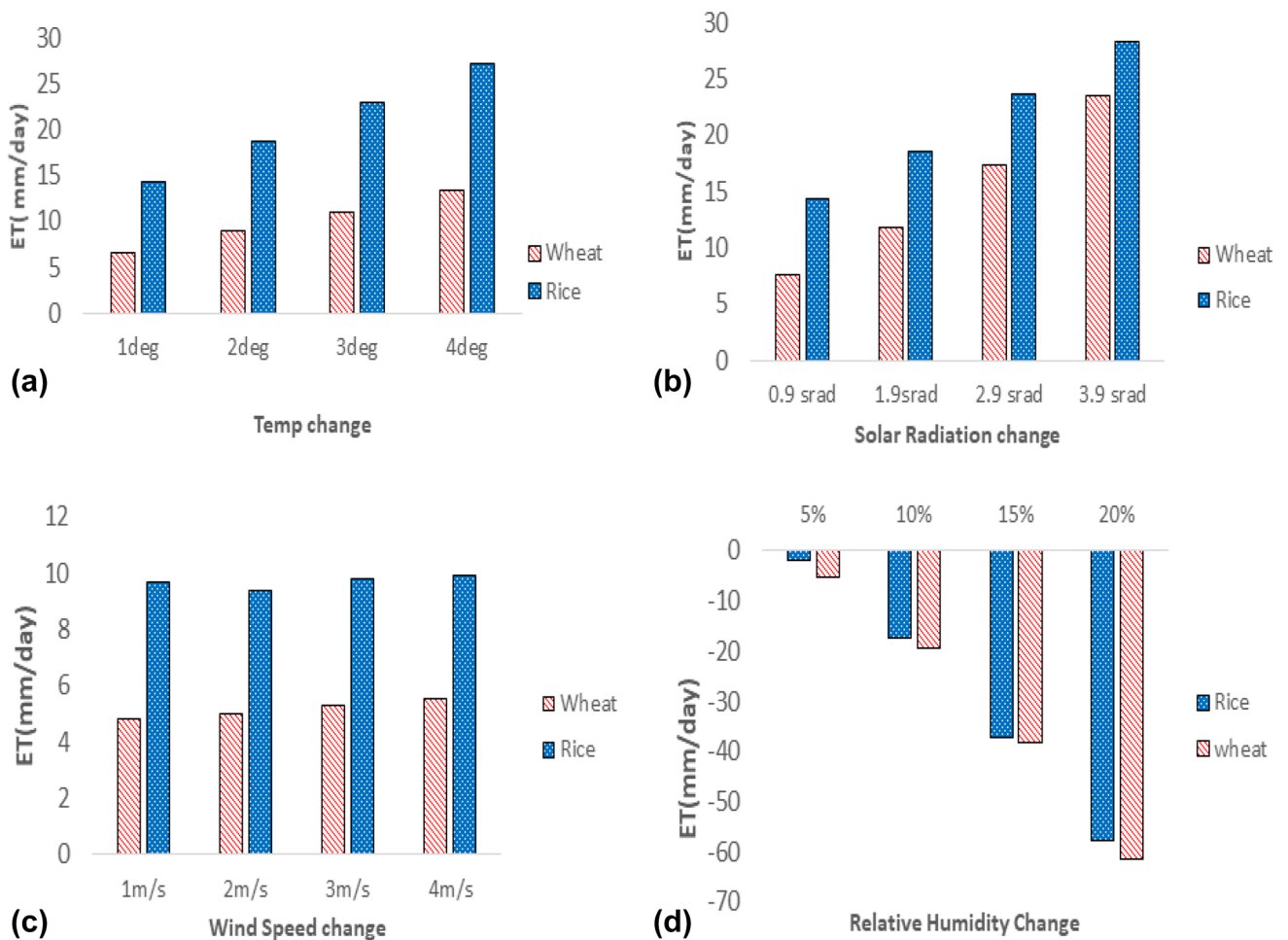


Fig. 5 Represents estimated percentage change in evapotranspiration of wheat and rice in response to expected changes in climate variables **a** temperature, **b** solar radiation, **c** wind speed, and **d** relative humidity

Table 2 Estimated change in Evapotranspiration (wheat and rice) in response to an increase in temperature by 10% and in combination 10% change in other weather parameter

% change	Max temp	Min temp	SRAD	WIND	RHUM	CO ₂	Max % change in ET for wheat	Min % change in ET for wheat	Max % change in ET for rice	Min % change in ET for rice
10%	✓	✓	✓	✓	✗	✗	215	2.8	55.5	19.4
	✓	✓	✓	✗	✗	✗	216	2.74	49.7	19.3
	✓	✓	✓	✓	✓	✗	169	0.53	32.8	11.2
	✓	✓	✓	✓	✓	✓	169.5	0.54	39.3	11.2
	✓	✓	✓	✗	✓	✓	169.6	0.54	32.8	4.1
	✓	✓	✓	✗	✗	✓	215	2.8	44.2	11.2
	✓	✓	✓	✓	✗	✓	216	2.75	44.2	11.1
	✓	✓	✓	✗	✓	✗	169.6	0.53	19.1	0.38
	✓	✓	✗	✓	✓	✓	141.6	0.43	18.64	0.8
	✓	✓	✗	✗	✓	✓	141.7	0.41	31.7	2.96
	✓	✓	✗	✗	✗	✓	193.8	3.7	55.1	19.8
	✓	✓	✗	✓	✗	✓	194.1	3.8	55	19.3
	✓	✓	✗	✓	✓	✗	141	0.42	32.9	2.57
	✓	✓	✗	✓	✗	✗	194.2	3.8	32.8	2.4
	✓	✓	✗	✗	✓	✗	141.7	0.41	19.4	0.32

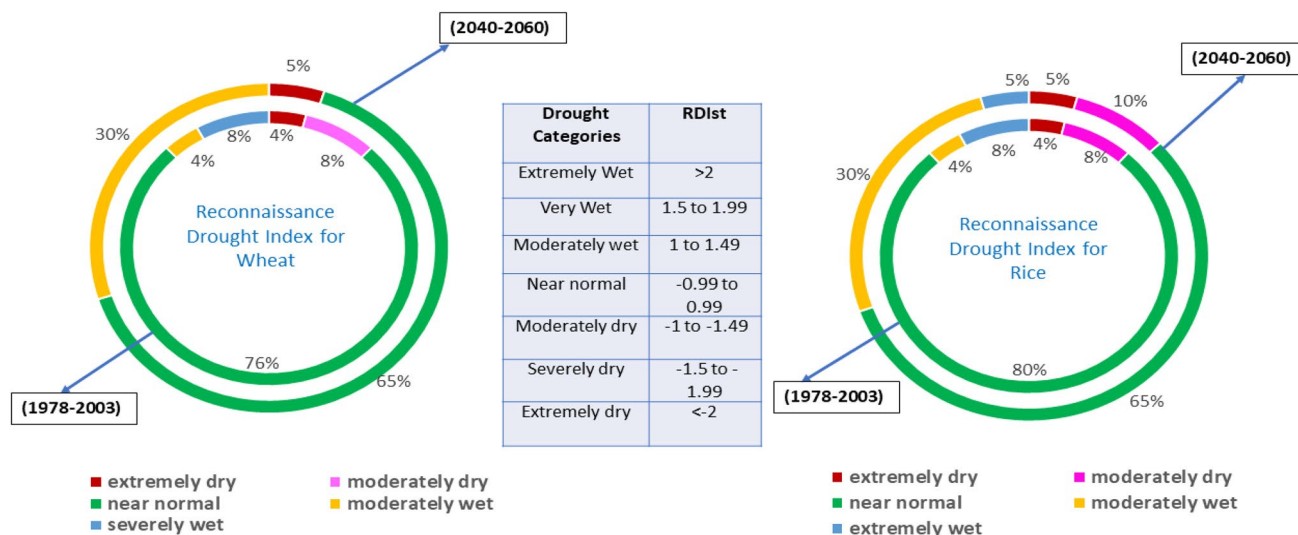


Fig. 6 Comparison of historical drought categories (1978–2003) to projected scenario (2040–2060) for wheat and rice based on RDIST Index

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