Spatio-temporal variability of temperature and potential evapotranspiration over India

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ABSTRACT

Worldwide, major changes in the climate are expected due to global warming, which leads to temperature variations. To assess the climate change impact on the hydrological cycle, a spatio-temporal change detection study of potential evapotranspiration (PET) along with maximum and minimum temperatures (T_{max} and T_{min}) over India have been performed for the second half of the 20th century (1950–2005) both at monthly and seasonal scale. From the observed monthly climatology of PET over India, high values of PET are envisioned during the months of March, April, May and June. Temperature is one of the significant factors in explaining changes in PET. Hence seasonal correlations of PET with T_{max} and T_{min} were analyzed using Spearman rank correlation. Correlation of PET with T_{max} was found to be higher compared to that with T_{min}. Seasonal variability of trend at each grid point over India was studied for T_{max}, T_{min} and PET separately. Trend Free Pre-Whitening and Modified Mann Kendall approaches, which consider the effect of serial correlation, were employed for the trend detection analysis. A significant trend was observed in T_{min} compared to T_{max} and PET. Significant upward trends in T_{max}, T_{min} and PET were observed over most of the grid points in the interior peninsular region.

Key words | correlation, non-parametric approaches, potential evapotranspiration, seasonal temperature, trend detection

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INTRODUCTION

Accurate hydro-climatological change detection study is essential, and has been considered as an emerging research field for the past couple of decades (Chattopadhyay & Hulme 1997; Hobbins *et al.* 2004; Espadafor *et al.* 2011; Fu *et al.* 2013). Long term spatio-temporal hydro-climatological change patterns provide valuable information for modeling various processes in hydrology, climatology, forestry and agriculture.

Evapotranspiration, which is one of the most significant components of the hydrological cycle, is influenced by meteorological conditions directly or indirectly. It is the union of evaporation and transpiration. Changes in meteorological variables due to climate change will affect evapotranspiration, which affects the crop water requirement, and subsequently water allocation for agriculture and food production (Zhang *et al.* 2011). Evapotranspiration is affected differently in different regions due to global warming. Determining the evaporation rate is essential for efficient management of water resources in a country like India. Long-term changes in potential evapotranspiration (PET) can have profound implications on hydrological processes as well as on agricultural crop performance (Hobbins *et al.* 2004). Liang *et al.* (2010) manifested the usefulness of study based on the temporal variation of PET in hydrological modeling, irrigation planning and water resources management.

As per Doorenbos & Pruitt's (1977) definition, 'the PET is the one that takes place when the ground is completely covered by actively growing uniform green grass of eight to fifteen centimeters tall in abundance of soil moisture'. Factors affecting PET are climatological data, crop factor

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and moisture level in the soil. Climatological data consist of surface air temperature, percentage of sunshine hours, wind speed, humidity, etc.

The fifth Intergovernmental Panel on Climate Change (IPCC) assessment report states that almost all regions of the world have experienced a heating process over the past half century (IPCC 2013). The fourth IPCC assessment report states that the surface air temperature has increased by $0.74 \pm 0.18\ ^{\circ}C$ during 1906 to 2005, and is also likely to increase during the 21st century (IPCC 2007). This could cause changes in the hydrological cycle (Bates *et al.* 2008). PET may be going to rise in most parts of the world in future because the water holding capacity of the atmosphere increases with higher temperature, i.e. about 7% per $1\ ^{\circ}C$ warming (Trenberth 2011), but relative humidity is not projected to change markedly. Consequently, the evaporation rate is likely to go up due to water vapor deficit. Thus historical PET analysis is of significant importance in the hydro-climatological perspective.

Extensive research has been carried out in different parts of the world (such as Australia, China, Gulf of Mexico, Northern Eurasia and Beijing) to assess the likely impact of climate change on PET (Helfer *et al.* 2012; Huo *et al.* 2013; Liu *et al.* 2013, 2014; Haijun *et al.* 2014). These studies reported that in the recent past the evapotranspiration change rate has increased considerably. Espadafor *et al.* (2011) found a significant increment in PET in southern Spain and inferred that the changes are mainly due to an increase in air temperature, solar radiation and a decrease in relative humidity. Tabari *et al.* (2011) ascertained the presence of a significant positive trend in annual evapotranspiration in the western half of Iran. They concluded that trend magnitudes are more intense in winter and summer compared to other seasons, and these variations are primarily because of significant increase in temperature. Zhang *et al.* (2013) inferred that the main causes for the decrease in reference evapotranspiration during 1960–1992 in China were the decrease in solar radiation in humid regions and decrease in wind speed in arid and semi-arid regions. Few studies ascertained that the effects of intensified temperature on evapotranspiration can be offset by the impact of other climatic variables (Chattopadhyay & Hulme 1997; Hobbins *et al.* 2004; Ramírez *et al.* 2005).

Roderick *et al.* (2007) mentioned that PET is an important indicator of global climate and environmental change owing to its close connection with key physical factors such as temperature, wind speed, solar radiation and humidity. A significant declining trend of surface solar radiation was observed over India during 1981–2004 (Kumari *et al.* 2007). Similarly, several studies focused on variations of solar radiation over different parts of the world and determined a decline of solar radiation (Wild 2009). Chattopadhyay & Hulme (1997) reported decreasing trends both in pan evaporation and PET in India from 1960 to 2000 in spite of an increment in temperature in the second half of the 20th century. But they also indicated that PET is going to rise unevenly in different seasons and regions of India in the future. Generally, an increasing trend is expected with increase in surface temperature. Despite the temperature increases, a large number of studies indicated a declining trend in PET (Jiang *et al.* 2011; Fu *et al.* 2013). This is known as the 'pan evaporation paradox' (Brutsaert & Parlange 1998; Hobbins *et al.* 2004). From literature, it can be inferred that the increase in relative humidity and decrease in radiation might be the main sources for this declining trend in PET over a few regions, whereas warming might cause a significant increasing PET trend in future.

Goyal (2004) detected that over the arid zone of Rajasthan in India, change in PET was highly sensitive to surface temperature followed by radiation, wind speed and vapor pressure during the last three decades of the 20th century. Nandagiri & Kovoor (2006) evaluated the performance of several approaches for reference evapotranspiration estimation both at daily and monthly timescales over different ranges of Indian climate. Their results were closer to the estimation by the Food and Agriculture Organization-56 Penman–Monteith approach. They reported that temperature based approaches have performed better than others, and the temperature-related variables appeared to be the most crucial inputs for evapotranspiration estimation across all Indian climates.

Bandyopadhyay *et al.* (2009) attributed the declining trend in wind speed to tall construction works. Decrease in reference evapotranspiration at annual and seasonal scales is observed in the north-east region of India (Jhajharia *et al.* 2012). A recent study by Jain (2012) on India's water balance and evapotranspiration suggested that the estimated evapotranspiration in India was much lower than anticipated with respect to changes in climate and land use, which may have major implications for India's water resources management.

The evaporative demand, a central process of the climate system, is expected to be altered along with the change in climate. In order to efficiently manage water resources, the amount of water used for irrigation needs to be properly organized. For this purpose, actual evapotranspiration (AET) assessment is needed. Although a lysimeter can be used for accurate measurement of evapotranspiration it is quite costly, which limits its usage. PET scores higher than AET in analyzing future changes as it can be obtained using a meteorological dataset. Evapotranspiration may vary perceptibly year to year with changing climate. Investigation on spatial and temporal variations of historical PET is useful in guiding present and future water management.

A few studies such as Khaliq *et al.* (2009) and Sonali & Nagesh Kumar (2013) have extensively reviewed various approaches for trend detection, and summarized the strengths and weaknesses of each of those approaches separately. Parametric, non-parametric, Bayesian and non-parametric with resampling approaches are generally used for performing trend analysis of time series data. Proper interpretation of data and relevant test assumptions are essential for conducting any statistical test. Parametric trend detection approaches require both independent and a particular (normal) distribution in the data, while non-parametric approaches only require the data to be independent. Hence non-parametric approaches have been widely used in trend detection analysis during the last couple of decades. But not all non-parametric approaches satisfy the independence assumption, and the presence of serial correlation enhances the type-I error. An improper assumption of independent observations could result in erroneous conclusions. So the effect of serial correlation should be considered in the case of hydrologic and climatic variables, which generally are serially correlated. Analysis by Khaliq *et al.* (2009) and Sonali & Nagesh Kumar (2013) strongly support the consideration of the effect of serial correlation in usual trend detection practice which is missing in most of the literature concerning India. But here a trend detection method, which considers the effect of serial correlation, is employed to deflect from spurious conclusions.

In spite of changing climate conditions, it is noticed that only a few studies are focusing on spatio-temporal change detection of PET over the whole of India compared to other parts of the world. Usually the influence of meteorological variables on PET change rate is region-specific. Moreover, in recent decades there has been a considerable increase in night time T_{min} compared to day time T_{max}. A consistent increasing trend was detected in T_{min} for most of the regions over India during the last three decades (Sonali & Nagesh Kumar 2013). Sonali & Nagesh Kumar (2016) found that most of the changes in T_{min} lie above the bounds of natural internal climate variability. This significant trend in T_{min} during recent decades could be considered as a signature of climate change over the whole of India (Sonali *et al.* 2016). T_{max} and T_{min} are among the six most commonly used variables for climate change impact assessment studies (IPCC 2001). Hence all these studies were motivated to analyze PET along with T_{max} and T_{min}. The present study mainly focused on long term spatio-temporal change detection. Short length data may lead to spurious conclusions in trend analysis. Based on the above discussion and availability of data (of different meteorological variables), the PET response to the changing climate from 1950 through 2005 (the second half of the 20th century) using T_{max} and T_{min} is studied.

Correlation assessments of PET with T_{max} and T_{min} are demonstrated. A spatio-temporal change detection study is performed separately for T_{max}, T_{min} and PET during each of the seasons. This study could provide useful information for improving the simulation of regional hydrometeorology. It could also be helpful for the policy-maker in the layout, development, utilization, management and protection of water resources in a sustainable and reasonable way.

Study region and data used

The whole of India is taken as the subject for the present study. Due to the non-availability of a historical dataset from the India Meteorological Department (IMD) (Srivastava *et al.* 2009), for the considered time period (i.e. 1950–2005), gridded historical monthly time series of T_{max}, T_{min} and PET from the latest version of the CRU3.21 dataset (developed by the Climatic Research Unit, which is a component of the university of East Anglia) has been used in this study (http://badc.nerc.ac.uk/browse/badc/cru/data/cru_ts/cru_ts_3.21, Harris *et al.* 2014). Data of these variables are available at $0.5 \times 0.5^{\circ}$ resolution.

The CRU3.21 data were interpolated to IMD grid points (which are available at $1 \times 1^\circ$ resolution), and absolute gridded average differences were obtained at annual, seasonal and monthly scales for both T_{max} and T_{min}. One of the most common spatial interpolation techniques, inverse distance weighting, is used here (Raju *et al.* 2016; Sonali *et al.* 2016; Sonali & Nagesh Kumar 2016). This is a standard deterministic interpolation approach in geographic information science, with easy and fast computation. The division into seasons considered here is based on conventional meteorological seasons defined by IMD (http://www.imdpune.gov.in/weather_forecasting/glossary.pdf), i.e. January–February (winter), March–May (pre monsoon), June–September (monsoon), October–December (post monsoon). Using these re-gridded datasets, the correlations and absolute gridded average differences were computed between the CRU3.21 and IMD datasets. This exercise was also repeated for all the months and all the seasons for both T_{max} and T_{min}. Consistently better correlation and lesser absolute gridded average differences are ascertained at all the grid points except a few (>30° North and >88° East), both at monthly and the seasonal timescale (Sonali *et al.* 2016). The same pattern has been observed for all seasons and months. The threshold of difference for excluding grids is more than 5 Kelvin (Sonali *et al.* 2016). Due to the significant differences, those grids were not considered further. In this analysis all the grid points, excluding the grid points beyond 30° North and 88° East, are considered. Most of the excluded grid points are located in the Western Himalaya region and partially in the north-east temperature homogenous region of India. Hence, in this study, the observed T_{max} and T_{min} dataset obtained from the CRU3.21 is used as a proxy to the IMD dataset.

None of the observed datasets are freely available for the validation of the gridded CRU3.21 PET dataset over the whole of India. But the CRU3.21 T_{max} and T_{min} dataset has ascertained better correlation with the IMD dataset (as explained above). Both T_{max} and T_{min} are among the most important parameters used in PET estimation. Hence the CRU3.21 PET dataset is used for the present analysis. The CRU3.21 PET dataset has been derived from a variant of the Penman–Monteith method (Allen *et al.* 1994). Gridded monthly averaged daily maximum, minimum and mean temperatures, vapor pressure and cloud cover datasets have been used for the estimation of the CRU3.21 PET dataset (Ekström *et al.* 2007).

METHODOLOGY

Initially the variations of PET climatology with respect to different months are obtained. Then Spearman rank correlation is used to assess the correlation of PET with T_{max} and T_{min}. Finally grid wise trend detection study is conducted to locate any significant changes in different considered variables. Depending on the availability and importance of the variable (as explained in the introduction section), spatio-temporal change detection of PET along with T_{max} and T_{min} have been analyzed for whole of India. PET is also sensitive to climatic variables such as solar radiation, relative humidity and wind speed along with temperature. Hence these different contributory sources to PET changes can be identified and studied in detail at different months and seasons in the future over the whole of India upon availability of data.

The most preferred statistical approaches from literature (in the presence of serial correlation) viz. Trend Free Pre-Whitening Mann Kendall (referred to as TFPW-MK), Modified Mann Kendall by Hamed & Rao (1998) (referred to as MMK-CF1) and Modified Mann Kendall by Yue & Wang (2004) (referred to as MMK-CF2) are employed for the present analysis. In both MMK-CF1 and MMK-CF2, the variance of the MK test statistic is multiplied by a correction factor, and hence they are known as variance correction approaches. All the trend detection approaches are evaluated at 5% significance level (α). Brief descriptions of the employed approaches are provided below.

MK test

The non-parametric rank based MK approach has been employed mostly to detect monotonic (linear/non-linear) trends in hydro-climatological time series (Mann 1945; Kendall 1975).

In this test, the null hypothesis of no trend is used to check against the alternative hypothesis of significant increasing/decreasing trend. The test statistic (S_{mk}) is defined as

$$S_{mk} = \sum_{i=2}^{n}\sum_{j=1}^{i-1} sign\ (x_i - x_j)$$

where n is the length of the data series, x_i and x_j are the sequential data in the series and

$$sign(x_i - x_j) = \begin{cases} -1 & for(x_i - x_j) < 0 \\ 0 & for(x_i - x_j) = 0 \\ 1 & for(x_i - x_j) > 0 \end{cases}$$

For sample size $n \geqslant 10$, MK test statistics are assumed to follow normal distribution. Mean and variance of S_{mk} are defined by

$$E[S_{mk}] = 0$$

$$Variance(S_{mk}) = \frac{n(n-1)(2n+5) - \sum_{k-1}^{q} t_k(t_k - 1)(2t_k + 5)}{18}$$

where t_k is the number of ties for the k^{th} value and q is the number of tied values. In the above formula for variance of S_{mk}, the second part of the numerator takes care of tied censored data.

The standardized test statistic Z_{mk} is defined as

$$Z_{mk} = \begin{cases} \dfrac{S_{mk} - 1}{\sqrt{Variance\ (S_{MK})}} & \text{if } S_{mk} > 0 \\ 0 & \text{if } S_{mk} = 0 \\ \dfrac{S_{mk} + 1}{\sqrt{Variance\ (S_{mk})}} & \text{if } S_{mk} < 0 \end{cases}$$

The significance level (α) is taken as a criterion for rejection of the null hypothesis. The null hypothesis, rejected at α level of significance in a two-sided test, implies that the standardized test statistic Z_{mk} is greater than $Z_{mk(1-\alpha/2)}$ obtained from the standard normal cumulative distribution tables.

Yue *et al.* (2002) found that pre-whitening alters the true slope present in the time series, and suggested TFPW to take care of the serial correlation effect in trend detection approaches. Hamed & Rao (1998) reported that the presence of serial correlation in a time series does not falsify either the asymptotic normality or mean of the MK test statistic S_{mk}, but the variance changes. Hence correction factors are proposed to correct the variance of S_{mk} using only those samples which are uncorrelated.

Sen's slope test

Similar to the parametric linear regression approach, Q_{sen} from the non-parametric Sen's slope (SS) approach shows both direction and magnitude of the trend in a time series (Sen 1968). The magnitude of the slope can be obtained as follows:

$$Q_{sen} = Median\left[\frac{(Y_i - Y_j)}{(i\ -\ j)}\right] for\ all\ j < i$$

where Y_i and Y_j are data at time points i and j, respectively. If the total number of data points in the series is n, then there will be $\frac{n(n-1)}{2}$ slope estimates. The test statistic Q_{Sen} is the median of all the slope estimates. Positive and negative signs of the test statistic represent increasing and decreasing trends, respectively.

TFPW-MK test

The TFPW-MK approach was suggested by Yue *et al.* (2002). This approach works with the assumption of the AR(1) process. In this approach, the slope (linear trend) of the time series using SS is calculated initially. Then the linear slope from the time series is de-trended. If the lag-1 correlation coefficient of the de-trended time series is significant at a defined level, then the MK test is applied to the de-trended pre-whitened series recombined with the estimated slope (using the SS approach), else the MK test is directly applied to the original series.

MMK-CF1 and MMK-CF2

The presence of positive (negative) serial correlation results in an increase (decrease) in the variance of MK test statistic S_{mk}. Hence, the variance correction approaches MMK-CF1 and MMK-CF2 were proposed by Hamed & Rao (1998) and Yue & Wang (2004), respectively. The modified variance of the MK test statistic is given by

$$Var(S_{mk})* = \mathrm{CF}{*}\mathrm{Var}(\mathrm{S_{mk}})$$

where CF is the correction factor. CFs proposed by Hamed & Rao (1998) and Yue & Wang (2004) are denoted as CF_1

and CF_2, respectively, and explained below.

$$CF_1 = 1 + \frac{2}{n(n-1)(n-2)} \sum_{k=1}^{n-1} (n-k)(n-k-1) \times (n-k-2) r_k^R$$

$$CF_2 = 1 + 2 \sum_{k=1}^{n-1} \left(1 - \frac{k}{n}\right) r_k$$

where r_k and r_k^R are the lag-k serial correlation coefficients of data and ranks of data, respectively, and n is the total length of the series. In this study both the MMK approaches are applied with the assumption of the AR(1) process.

RESULTS AND DISCUSSION

Results and discussion are explained in three parts.

Monthly climatology of PET

Climatology is the averaged weather condition over a period of time. The magnitude and spatial distribution of global PET is highly uncertain (Douville *et al.* 2013). For the present analysis, the monthly climatology study of PET is the first step. The climatology of PET with respect to the considered period (1950–2005) has been obtained for each month individually. Results are shown in Figure 1 for each of the 12 months, i.e. January to December separately. PET rates are expressed in millimetres per month. It can be seen that in the months of March, April, May and June, rates of PET are high compared to other months, whereas in the months of November and December these are lower. In north central, north-west and some portions of the interior peninsular regions, PET rates are very high compared to other parts of India during the months of April, May and June. Uncertainty in PET has been manifested during the second

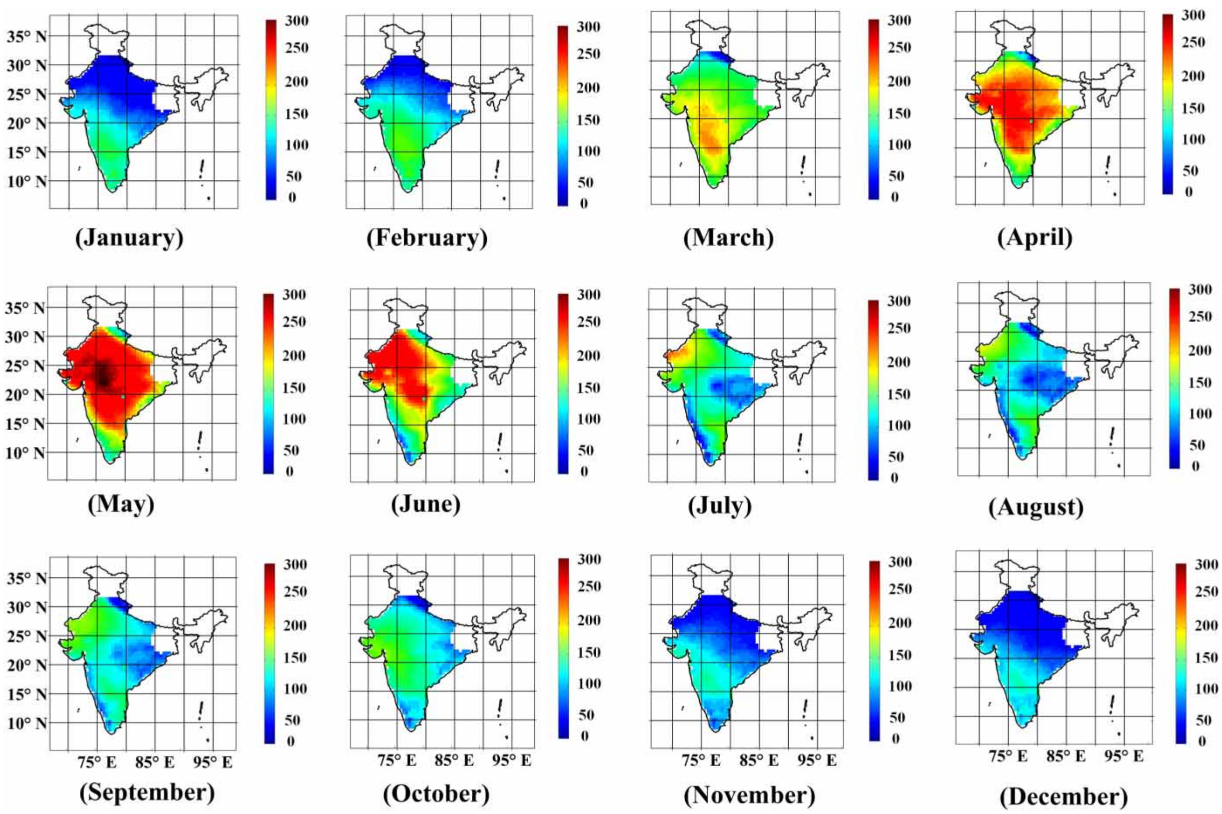

Figure 1 | PET (mm per month) variation in different months (January–December) during 1950–2005.

half of the 20th century in India, which is evident from the plots in Figure 1. Hence further evaluation of the spatio-temporal variability of PET is essential for effective water resources management.

Correlations: PET and T_{max} and PET and T_{min}

In the second step, the study analyzes the correlation of PET with T_{max} and T_{min} to assess their linkages and to observe

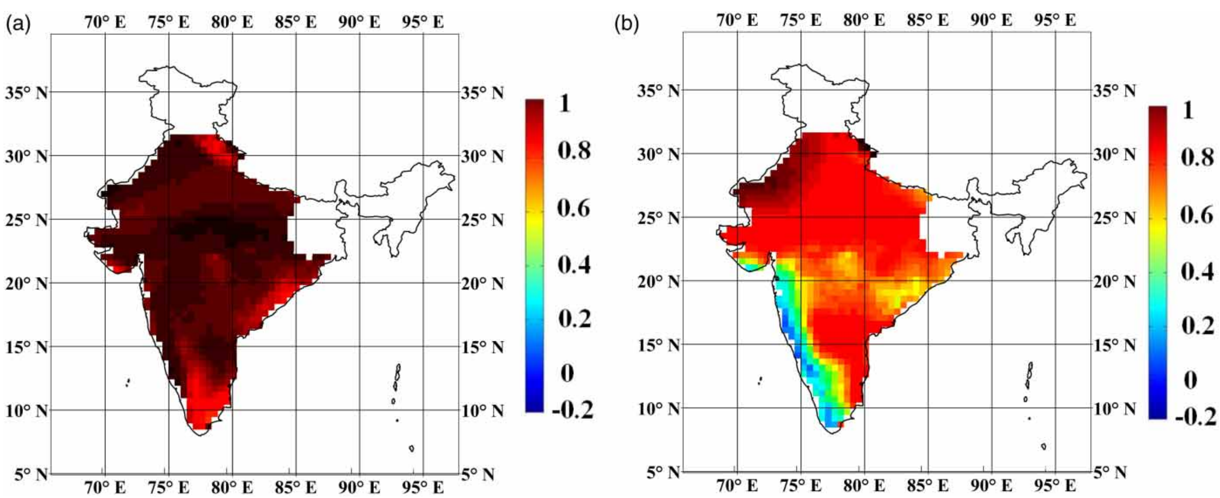

Figure 2 | Correlation between (a) PET and T_{max} and (b) PET and T_{min}.

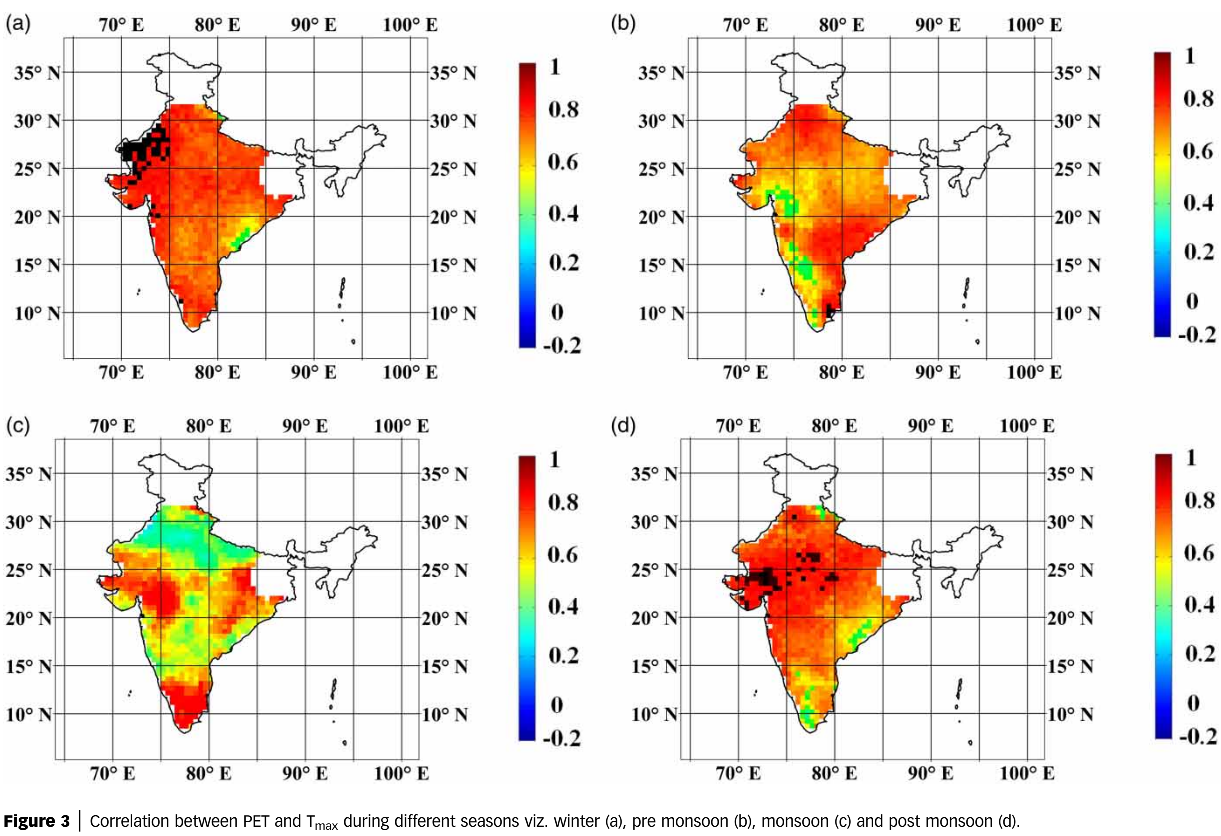

Figure 3 | Correlation between PET and T_{max} during different seasons viz. winter (a), pre monsoon (b), monsoon (c) and post monsoon (d).

the patterns in different seasons and regions over the whole of India. Correlation is determined individually for T_{max} and T_{min} with PET by considering all months together and also for the considered four seasons. The non-parametric Spearman rank correlation is used to conduct the correlation analysis. This is less sensitive to outliers (as it considers rank instead of magnitude) compared to the Pearson correlation. It measures the monotonic relationship (either linear or non-linear). It takes care of duplicate values existing in the time series.

The results of correlation analysis are shown in Figure 2, considering the whole time series (all months' data together). Subplots 'a' and 'b' in Figure 2 are, respectively, for T_{max} and T_{min} for their correlations with PET at monthly timescale. Although both T_{max} and T_{min} possess significant correlation with PET, T_{max} is better correlated compared to T_{min}.

Similar analysis has been conducted individually for each season. Results from seasonal correlation analysis for T_{max} and T_{min} are shown in Figures 3 and 4, respectively. In both these figures, sub plots 'a', 'b', 'c' and 'd' are for different seasons, viz. winter, pre monsoon, monsoon and post monsoon, respectively. For all the seasons, PET has a better correlation with T_{max} compared to T_{min}. The correlation between PET and T_{max} is very high during all the seasons except for the monsoon season. The hydro-climatological pattern during monsoon season is highly uncertain in nature. It is tough to interpret, as it represents dynamic interactions between atmosphere, ocean and continents.

Grid wise temporal variability of PET, T_{max} and T_{min}

Analysis of PET trends and its driving climatic factors can provide scientific insights for improving water management, especially under predicted climate change. Assessment of T_{max}, T_{min} and PET spatio-temporal variabilities is useful in terms of hydro-climatological perspective. Here in the third step, trends in PET, T_{max} and T_{min} are investigated through TFPW-MK and MMK approaches. Using the Kolmogorov–Smirnov test, it is observed that none of the time series

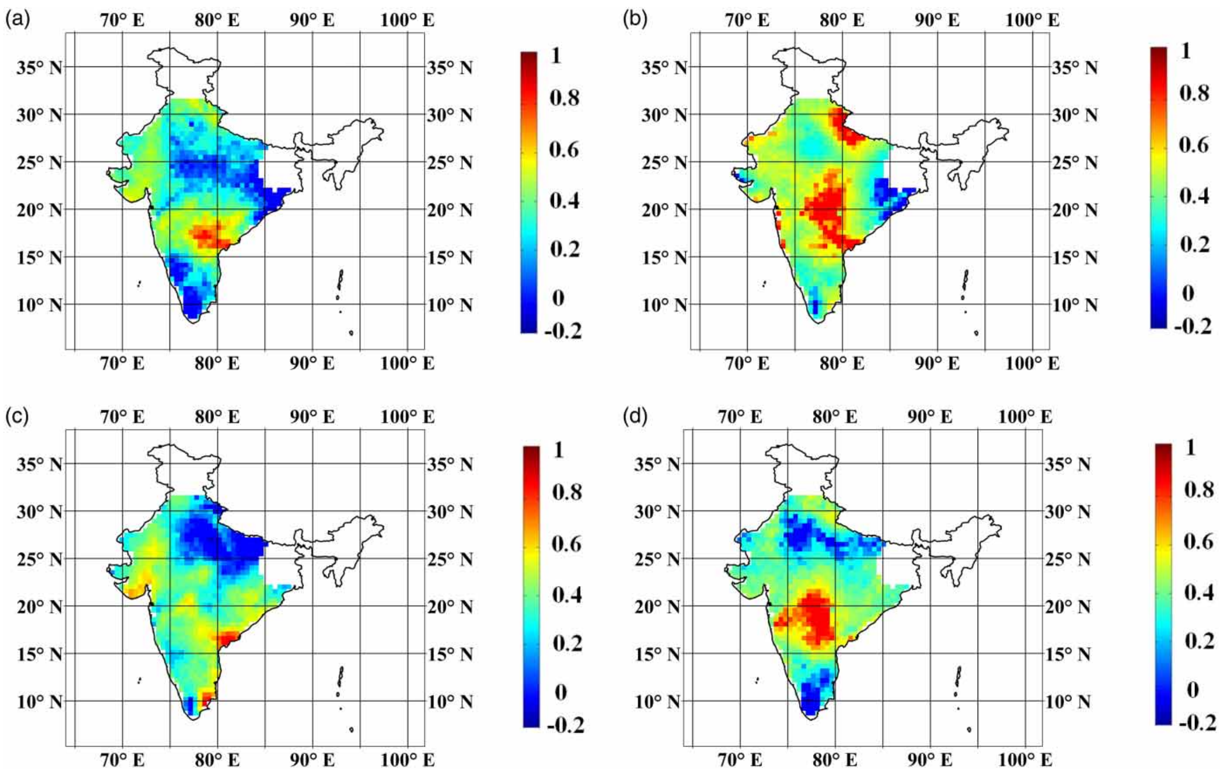

Figure 4 | Correlation between PET and T_{min} during different seasons viz. winter (a), pre monsoon (b), monsoon (c) and post monsoon (d).

(over all the grid points) are following a normal distribution. Hence there is no scope of parametric approaches for this trend detection analysis. Trend detection analysis was conducted individually for the three considered parameters, viz. T_{max}, T_{min} and PET, for the same time period (1950–2005). This exercise is repeated for four different seasons separately. As mentioned earlier, 5% significance level is considered for all trend detection approaches.

Analysis is repeated using each of the three considered trend detection approaches. Good agreement is found between all the implemented approaches. In all the correction approaches, i.e. MMK-CF1, MMK-CF2 and TFPW-MK, proper care has been taken to locate both positive and negative correlations. As discussed, pre-whitening has a problem in maintaining the important feature of a statistical test, the nominal significance level. It also affects the magnitude of true slope of a time series (Khaliq *et al.* 2009). Hence TFPW-MK, an improved version of pre-whitening developed for serial correlated data, is employed in this study.

Trend detection analysis results are shown in Figures 5–7, respectively, for T_{max}, T_{min} and PET. Subplots 'a' to 'd' represent different seasons, viz. winter, pre monsoon, monsoon and post monsoon, respectively. In Figures 5–7, the maroon color indicates a significant upward (positive) trend, the yellow color indicates no trend and the cyan color indicates a significant downward (negative) trend (the full color version of this figure is available in the online version of this paper, at http://dx.doi.org/10.2166/wcc.2016.230).

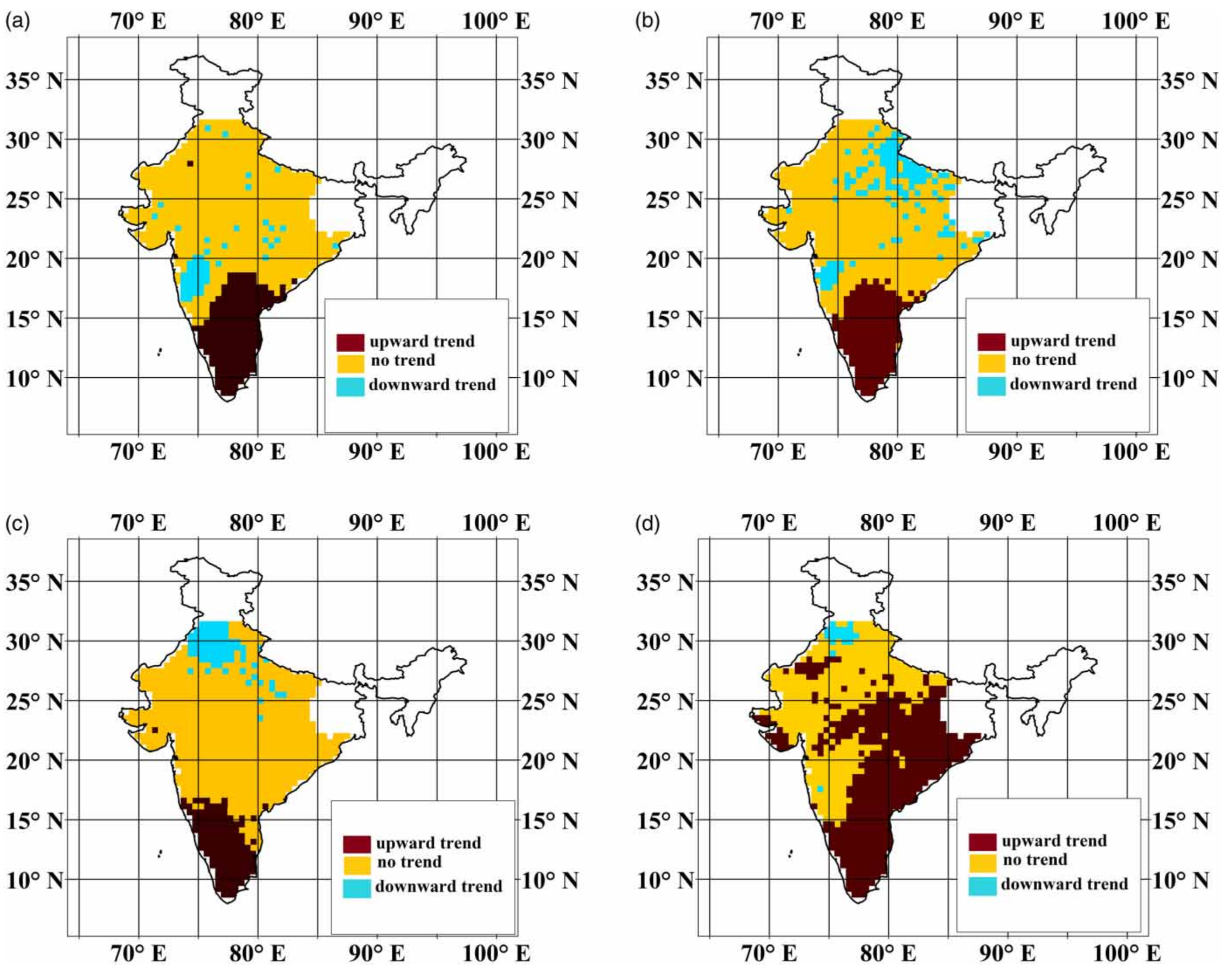

Figure 5 | Trend in T_{max} during different seasons viz. winter (a), pre monsoon (b), monsoon (c) and post monsoon (d). The full color version of this figure is available in the online version of this paper, at http://dx.doi.org/10.2166/wcc.2016.230.

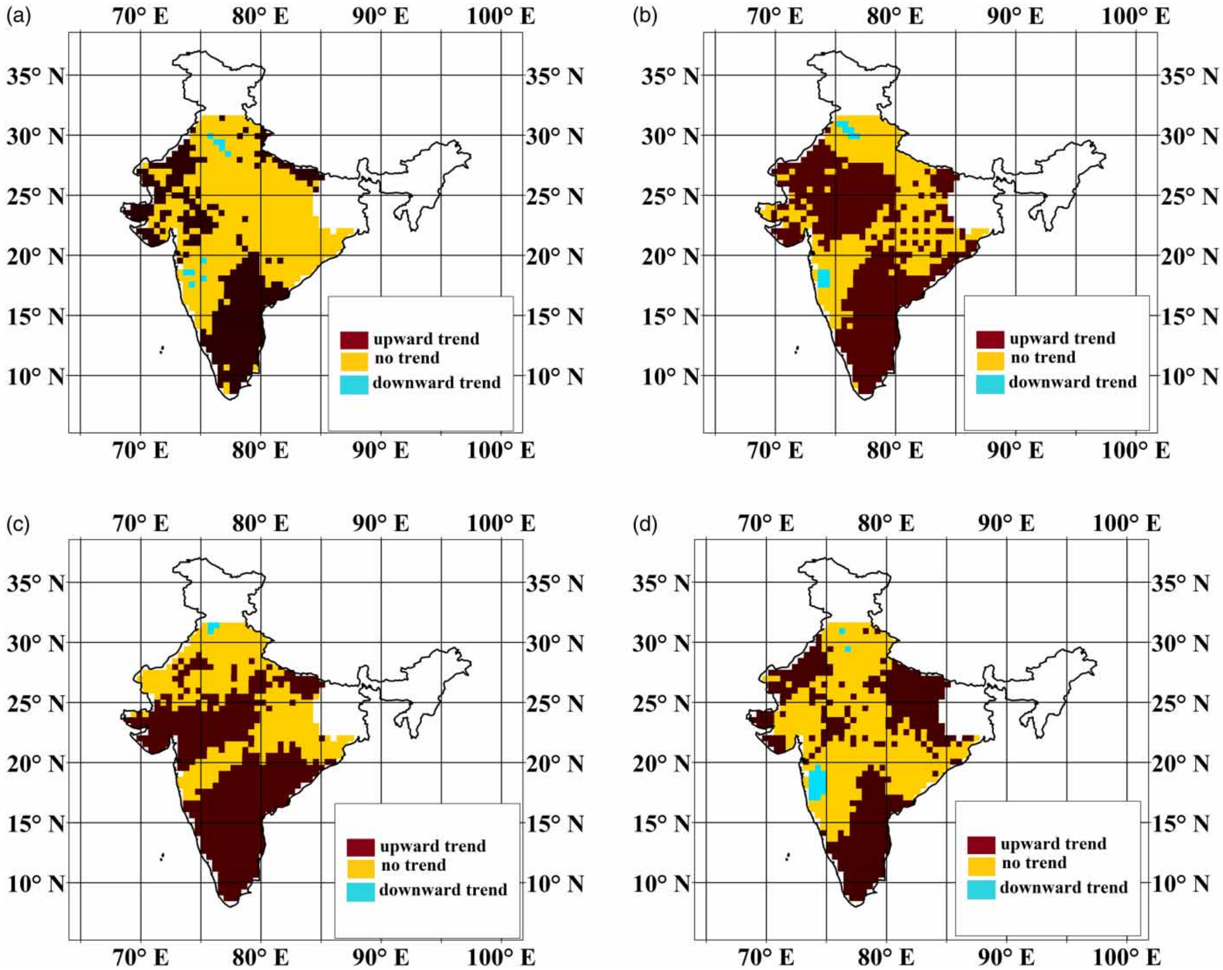

Figure 6 | Trend in T_{min} during different seasons viz. winter (a), pre monsoon (b), monsoon (c) and post monsoon (d). The full color version of this figure is available in the online version of this paper, at http://dx.doi.org/10.2166/wcc.2016.230.

There are more grid points with significant upward trend for T_{min} compared to T_{max} and PET in all the seasons except post monsoon. In post monsoon, the number of grid points with significant upward trend is greater compared to the other seasons for both T_{max} and PET.

The total number of grid points with significant upward trend is fewer in winter for T_{min} compared to other seasons. Significant upward trends in T_{max}, T_{min} and PET are observed over most of the grid points covering the interior peninsular region of India during all four seasons, except PET in the monsoon and pre monsoon seasons. Grid points with significant downward trend are fewer for T_{min} than for PET in all four seasons. In pre monsoon and monsoon, the number of grid points with significant upward trend is very high for T_{min}. Temperature is one of the significant factors in explaining changes in PET. In spite of the high seasonal correlation between PET and T_{max}, the spatio-temporal variability patterns do not entirely match. T_{max} varies greatly during post monsoon, but no proportional change is observed in PET.

Significant upward trends in T_{min} establish a signature of climate change that has already been verified by the previous studies by Kothawale & Rupa Kumar (2005) and Sonali & Nagesh Kumar (2013). Even though there is a significant rise in both T_{max} and T_{min}, PET has declined over some of the grids. This tendency may be because of a decrease in wind speed, net radiation and to some extent due to the saturation vapor pressure deficit, which has already been reported in

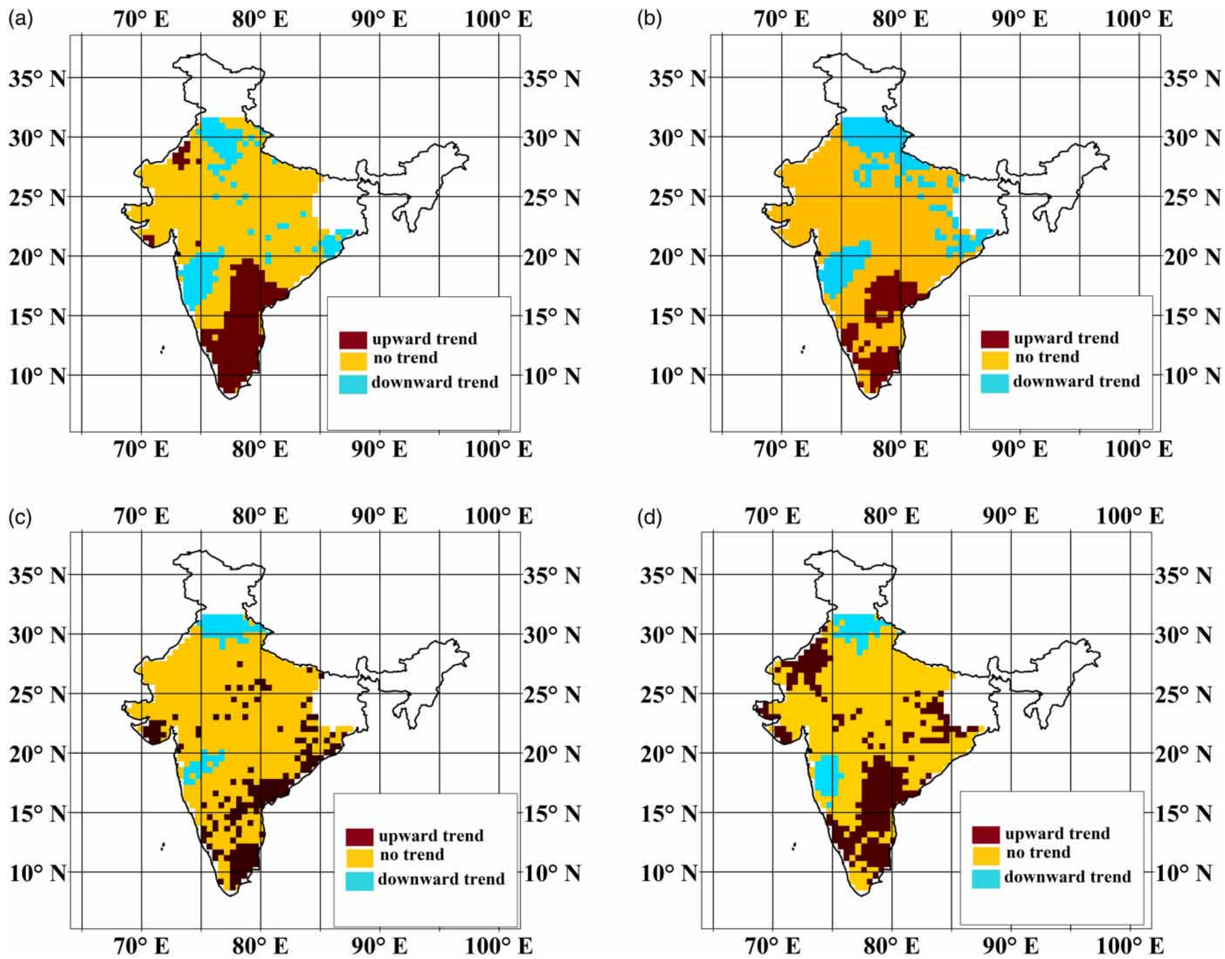

Figure 7 | Trend in PET during different seasons viz. winter (a), pre monsoon (b), monsoon (c) and post monsoon (d). The full color version of this figure is available in the online version of this paper, at http://dx.doi.org/10.2166/wcc.2016.230.

many former studies for different parts of the world along with India (Chattopadhyay & Hulme 1997; Zhang *et al.* 2013). In future, wind speed, net radiation and saturation vapor pressure can also be considered for a detailed assessment of change in PET over India. Currently, due to unavailability of these datasets, spatio-temporal change in PET is studied with respect to only T_{max} and T_{min}.

CONCLUSIONS

Change in climate is likely to have a profound effect on different components of the hydrological cycle. Evapotranspiration is one among them. Evapotranspiration is likely to be affected by global warming because of its dependence on surface temperature. As explained, PET is the amount of evapotranspiration in an abundance of water supply. Changes in PET over space and time provide a clearer picture about the movement of the water cycle (Bates *et al.* 2008). Evaluation of the spatio-temporal variability of PET, T_{max} and T_{min} was the primary focus of this study. Long-term gridded datasets of PET along with T_{max} and T_{min} from CRU were used to perform the spatio-temporal change detection analysis over all India, except most parts of the Western Himalaya and the north-east region.

Monthly climatology patterns for PET were obtained. The results confirmed a higher PET rate during the months of March, April, May and June. A high correlation of PET with T_{max} was observed both at monthly as well as seasonal scales. Hence, temperature is one of the significant factors in explaining changes in PET. The change in PET, T_{max} and T_{min} from 1950 to 2005 in India was analyzed for all four seasons (winter, pre monsoon, monsoon and post monsoon) using MMK and TFPW-MK approaches. A significant trend was observed in T_{min} when compared with T_{max} and PET. The present assessment, in line with previous studies, concluded that even though there is a significant increase in both T_{max} and T_{min} (T_{min} being greater), grid points with significant upward trend are fewer in number in the case of PET. Major changes in various components of the hydrological cycle are expected in response to global warming (Huntington 2006). But the effect of temperature is offset by other significant parameters that influence PET. Significant positive trends in T_{max}, T_{min} and PET were observed over most of the grid points in the interior peninsular region. Overall, the trend in PET showed substantial spatial and temporal heterogeneities over all India during the second half of the 20th century. This study provides a broad vision of water resources planning and management by analyzing the change in PET along with temperature. These historical correlation assessment results might hold good in the future, and can be used further for future projections with respect to different scenarios. Also, findings from this analysis could be utilized further in hydro-climatological study, and can also provide extra inputs for optimized estimation of crop water requirement at a broad scale during different seasons.

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