Effect of de-trending climatic parameters on temporal changes of reference evapotranspiration in the eastern Himalayan region of Sikkim, India

Vanita Pandey, Indira Taloh and P. K. Pandey*
Department of Agricultural Engineering, North Eastern Regional Institute of Science and Technology (NERIST), Nirjuli, Itanagar, Arunachal Pradesh, India
*Corresponding author. E-mail: pkpnerist@gmail.com

ABSTRACT

Reference Evapotranspiration ($ET_0$) is an essential factor in irrigation scheduling, climate change studies, and drought assessment. The study’s main objective was to identify the influences of detrending input climatic parameters (CPs) on $ET_0$ using linear and nonlinear approaches throughout 1980–2015 in Gangtok, East Sikkim, India. The benchmark values of $ET_0$ were calculated using the global standard FAO56 Penman–Montieth equation. The $ET_0$-related CPs included for the analysis are maximum temperature ($T_{\text{max}}$), minimum temperature ($T_{\text{min}}$), maximum relative humidity ($RH_{\text{max}}$), minimum relative humidity ($RH_{\text{min}}$), and sunshine duration (SSH). The linear and nonlinear trends in various CPs affect $ET_0$ change. Linearly detrended series was obtained by linear regression method whereas, nonlinearly detrended series was obtained using the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise method. Twenty-three scenarios, including the original scenario, 11 scenarios in Group 1 (CPs de-trended linearly), and 11 scenarios in Group 2 (CPs de-trended nonlinearly) were generated. Inflences of $T_{\text{max}}$ and SSH were more substantial than the influences of other CPs for both Group 1 and Group 2. The SSH masked the weak influence of other CPs. The effects of the trends in CPs, especially of SSH and $T_{\text{max}}$, were clearly shown. The $ET_0$ values decreased significantly during 1980–2015; however, no significant decreasing trend was observed in the case of SSH, during the same period. The nonlinear detrending gave closer results to the benchmark values as compared to linear detrending because of non-monotone variations of the $ET_0$ and CPs. Therefore, the results from nonlinear detrending were more plausible as compared to linear detrending. The diminishing trend of $ET_0$ prompted an overall alleviation of the dry spell, hence there would be a somewhat lower risk of water use in the study region.

Key words: CEEMDAN, climatic parameters (CPs), linear and nonlinear detrending, reference evapotranspiration ($ET_0$)

HIGHLIGHTS

- Sunshine hour (SSH) and maximum temperature ($T_{\text{max}}$) independently were the most important variables affecting reference evapotranspiration ($ET_0$).
- Detrending of minimum temperature and relative humidity insignificantly affects the $ET_0$ process.
- Effect of detrending sunshine hour (SSH) masked the increasing trend effects of other climatic parameters on $ET_0$.
- $ET_0$ estimated by nonlinear detrending of climatic parameters (CPs) was satisfactory and convincing compared to linear detrending.

INTRODUCTION

Climate-related risks to food security, agriculture, livelihoods, and water supply are anticipated to increment with global warming of 1.5 °C above temperatures in the pre-industrial period and increment further with 2 °C by 2100 (Intergovernmental Panel on Climate Change (IPCC 2019)). In the context of global warming and climate change, accurate estimation and prediction of evapotranspiration is of vital importance in the studies related to hydrological modeling, climate change prediction, water resources planning and management, irrigation scheduling, and determining crop water requirement. The reference evapotranspiration ($ET_0$) can be used as an index to assess agricultural water demand. The FAO had identified the FAO56 Penman–Montieth (FAO56-P-M) model as a benchmark for the precise estimation of $ET_0$ following an extensive comparison with lysimetric measured data globally (Allen et al. 1998).
A literature survey confirms that studies worldwide reported that the trend of ET₀ was found to have increased or decreased in various areas of the world. Studies reported both increasing and decreasing trends in Iran (Dinpashoh et al. 2011), China (Mo et al. 2017; Liu et al. 2020), and India (Sonalī & Nagesh Kumar 2016). Significant increasing trends of ET₀ were reported in the Korean Peninsula (Ghafouri-Azar et al. 2018), in Iran (Aizzadeh & Javan 2015), in central Europe (Zaninović & Gajić-Ćapka 2000), and China (Niu et al. 2019). The strong decreasing trend in ET₀ was observed in Canada (Burn & Hesch 2007), in the United States (Golubev et al. 2001), in Australia (Donohue et al. 2010), in India (Verma et al. 2008; Jhajharia et al. 2012; Yadav et al. 2016; Goroshi et al. 2017), and in China (Niu et al. 2019).

The reference evapotranspiration is a multivariate parameter and function of climatic parameters (CPs), namely temperature (T), relative humidity (RH), solar radiation (Rs), and wind speed (Ws). The temporal variability of CPs is mainly responsible for the upward and downward trend in ET₀ (Li et al. 2017). The analysis of impacts of CPs on ET₀ is useful to know the climatic change impacts on ET₀ (Xu et al. 2006; McVicar et al. 2012). There are two conventional approaches to quantify the influence of CPs on ET₀. The first approach is based on sensitivity analysis (Mckenney & Rosenberg 1993; Tabari & Hosseinzadeh Talaei 2014; Zhao et al. 2014; Patle & Singh 2015), while the second method re-calculates ET₀ by using detrended CPs (Huo et al. 2013; Zhao et al. 2014; Li et al. 2017). However, these studies analyzed only the impacts of the single climatic parameter on ET₀, not the simultaneous effects of different factors on ET₀. Since CPs change simultaneously, a single CP such as a different temperature (maximum T(max) and minimum T(min)) may vary in a different pattern. It is not sufficient to know only the influences of a single CP on ET₀. Studies mentioned above have not recognized the influence of different temperature factors (T(min) and T(max)) on ET₀. Additionally, eliminating linear trends from CPs is sufficient, yet eliminating the nonlinear trend in CPs is vital because most CPs change nonlinearly with time.

Statistical trend analysis can be further carried out under parametric and nonparametric analysis. The difference between the two is the way of using collected data. In the parametric analysis, actual parameters are used to determine the trend, considering data are normally distributed and independent. However, the nonparametric test does not necessarily require data to be normally distributed. The most often utilized nonparametric test for identifying the pattern in data is the Mann–Kendall test (Kahya & Kalayci 2004; Jayawardene et al. 2005; Burn & Hesch 2007; Li et al. 2007; Thepprasit et al. 2009; Aksu et al. 2010; Espadafor et al. 2011; Tabari & Marofi 2011; Jhajharia et al. 2012; Karmeshu 2012; Kousari & Ahani 2012; Shadmani et al. 2012; Gocic & Trajkovic 2014) to detect the trend in climatic time series.

Before implementing any parametric or nonparametric tests, the data's independence should be checked using the lag-1 autocorrelation test. The trend-free pre-whitening with Mann–Kendall is one common approach, which shows the relation between a linear trend and a lag-one autocorrelation (Yue et al. 2002, 2003; Dinpashoh et al. 2011). The elimination of trend components before pre-whitening removes the serial correlation from the time series. The elimination of positive serial correlation components through pre-whitening causes the magnitude of the prevailing trend to reduce. In their variance correction approach, Hameed & Rao (1998) reported that the existence of positive or negative serial correlation results in an increase or decrease in the variance of Mann–Kendall test statistic (S). Therefore, to prevent the effect of the problem, the variance correction approach was recommended.

Detrending is a mathematical or statistical operation of removing trends from a climatic time series. The detrending technique is a combined methodology that considers both the sensitivity coefficient and the rate of climatic factors. The empirical mode decomposition (EMD) is a versatile technique developed to examine non-stationary and nonlinear signals. It comprises a nearby and completely information-driven detachment of a signal in rapid and moderate oscillations. The decomposition is produced from the traditional assumption that any data consist of oscillation's various basic intrinsic modes.

Every mode might be linear and may have a similar number of extrema and zero intersections. However, EMD encounters a few issues, such as oscillation of unique amplitude in a mode of the existence of fundamentally the same oscillations in various modes, called ‘mode mixing.’ Torres et al. (2011) suggested an ensemble empirical mode decomposition (EEMD) with the addition to Gaussian white noise over EMD. The addition of Gaussian white noise eliminates the problem of mode mixing (Guo et al. 2016). Sang et al. (2014) in a comparison of the Mann–Kendall and EMD method of trend analysis reported that EMD can be an effective alternative for trend identification of hydrological time series. Even though EEMD by then was proven to help investigate
geophysical data, it additionally has a few disadvantages. The main disadvantage is that the signal reproduced by EEMD has a residual noise, and the problem of mode mixing still exists in outermost applications to real data. Antico et al. (2014) developed the CEEMDAN (complete ensemble empirical mode decomposition with adaptive noise) method. The CEEMDAN gives an accurate reconstruction of the original signal and an apparent spectral detachment of modes, thus eliminating the mode mixing problem (Antico et al. 2014; Marusiak & Pekar 2014). Antico et al. (2014) successfully applied CEEMDAN on river discharge data to determine the time-scale components of hydrological time series and concluded that it is the powerful method for extracting physically meaningful information from hydroclimatic data. Therefore, CEEMDAN is a powerful means for separating physically relevant data from hydroclimatic time series, particularly when the previously mentioned issues are experienced.

The authors did not find the same or at least similar earlier conducted studies which analyzed the influence of removing both (linear and nonlinear) trends from various CPs on ET₀ in India. In this case study, we performed a trend analysis of different CPs. In the next step, CPs are detrended both linearly and nonlinearly to study the effect of detrending the CPs on temporal variations of annual reference evapotranspiration (ET₀) Gangtok, Sikkim.

**METHODS**

**Description of the study area and data sets**

The study area is situated in the eastern Himalayas, according to the agro-climate zone of India (Government of India 1989). The investigation was conducted in east Sikkim, which has a latitude range between 27°9' and 27°23' N and longitude from 88°27' and 88°56' E, and covers about 900 km² area. Geographically, East Sikkim occupies the southeast corner of the state (Figure 1). Almost the entire east Sikkim is hilly, with an elevation range of 811–1,650 m. The average annual sum of the precipitation during the observed period at Gangtok is about 3,090 mm. The average annual temperatures (Tmax and Tmin) during the observed period were 22.97 and 13.72 °C, respectively (Table 1). The district’s average index of wetness is more than one, and the number of rainy days ranges from
128 to 205 days. The study region gets a significant part of precipitation from the south-west monsoon. For most periods in the course of a year, the climate is cold and humid as precipitation occurs each month. Pre-monsoon rain occurs in April–May, and monsoon (south-west) operates normally from May and continues up to early October. The descriptive statistics of ET0 and different meteorological parameters are depicted in Table 1.

**Modeling of reference evapotranspiration (ET0)**

The FAO 56 Penman–Monteith (FAO56-P-M) (Allen et al. 1998) equation is used as the standard method for the computation of ET0 from meteorological data. The mathematical equation of the FAO56-P-M, ET0 can be written as:

\[
ET_0 = \frac{0.408 \Delta (R_{net} - G_{dir}) + \gamma \frac{900}{T + 273} W_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 W_2)}
\]

where ET0 is reference evapotranspiration (mm d\(^{-1}\)), \(R_{net}\) is net radiation (MJ m\(^{-2}\) d\(^{-1}\)), \((e_s - e_a)\) is difference between the saturation vapor pressure \(e_s\) (kPa) and the actual vapor pressure \(e_a\) (kPa), \(\Delta\) is the slope of the saturation vapor pressure–temperature curve (kPa °C\(^{-1}\)), \(\gamma\) is the psychrometric constant (kPa °C\(^{-1}\)), \(W_2\) is the wind speed at 2 m height (m s\(^{-1}\)), \(T\) is the average air temperature (°C), and \(G_{dir}\) is the monthly soil heat flux density (MJ m\(^{-2}\) d\(^{-1}\)). The detailed procedure for estimating different secondary parameters of FAO-56-P-M can be found elsewhere (Allen et al. 1998).

**Data management for analysis**

The daily meteorological data from 1980 to 2015 for various CPs namely \(T_{max}\) (°C), \(T_{min}\) (°C), \(RH_{max}\) (%), \(RH_{min}\) (%) and SSH (h) to apply FAO56-P-M were collected from the Indian Meteorological Department, Tadong, Sikkim. The mean monthly and seasonal ET0 was estimated using the FAO56-P-M equation. The baseline values were fixed as mean values of monthly, seasonal ET0, and CPs.

**Trend and change point (TAC) analysis**

The CPs, namely \(T_{max}\) (°C), \(T_{min}\) (°C), \(RH_{max}\) (%), \(RH_{min}\) (%), SSH (h), and ET0 (mm d\(^{-1}\)), were used for trend and abrupt change year (TAC). The modified nonparametric Mann–Kendall (MM-K) (Yue & Wang 2004) was used for
trend analysis. The MM-K statistics ($Z_c$) can be estimated using the Mann–Kendall method (Mann 1945; Kendall 1975) by eliminating the influence of serial autocorrelation in $x_i$ ($i = 1, 2, 3 \ldots n$, where $n$ is the total number of years). The correction in MM-K statistics $Z_c$’s variance was performed, as in Hameed & Rao (1998) and Sonali & Nagesh Kumar (2013).

\[ \text{Var}^*(Z) = \frac{n}{n^*} \text{Var}(Z) \]  

(2)

where $n$ is the number of data points, $n^*$ is the effective sample size, and $n/n^*$ is the correction factor for serial correlation in sample data, $\text{Var}(Z)$ is the variance of $Z$ of MK (Mann–Kendall) statistic for the time series, estimated using the following relationship:

\[ \text{Var}(Z) = \frac{n \times (n - 1) \times (2n + 5)}{18} \]  

(3)

The existence of tied ranks (equal observations) in the data results in a reduction of the variance of $Z$ to become,

\[ \text{Var}(Z) = \frac{n \times (n - 1) \times (2n + 5)}{18} - \frac{1}{n} \sum_{i=1}^{k} T_i \times (T_i - 1) \times (2T_i + 5) \]  

(4)

where $k$ is the number of groups of tied ranks, each with $T_i$ tied observations.

The correction factor $n/n^*$ in Equation (2) can be estimated as:

\[ \frac{n}{n^*} = 1 + \frac{2}{n(n - 1)(n - 2)} \sum_{l=1}^{n-1} (n - l)(n - l - 1)(n - l - 2) \tau_l^R \]  

(5)

where $\tau_l^R$ is the lag-$l$ serial correlation coefficient of rank $R_{X_t}$ of the sample data $X_t$. Salas et al.’s (1980) equation given below is used for estimating values $\tau_l^R$ by substituting the sample data $X_t$ by their ranks $R_{X_t}$.

\[ \tau_1 = \frac{1}{n - l} \sum_{s=1}^{n-l} [X_s - E(X_s)] [X_{s+l} - E(X_s)] \]  

\[ + \frac{1}{n} \sum_{s=1}^{n} [X_s - E(X_s)]^2 \]  

(6)

\[ E(X_s) = \frac{1}{n} \sum_{s=1}^{n} X_s \]  

(7)

where $\tau_1$ is the serial correlation coefficient at lag1 of the sample ($X_s$), and $E(X_s)$ is the mean of the sample.

The modified standardized MK statistic $Z_c$ can be estimated as

\[ Z_c = \begin{cases} 
\sqrt{\text{Var}^*(Z)} & \text{if } Z > 0 \\
0 & \text{if } Z = 0 \\
-\sqrt{\text{Var}^*(Z)} & \text{if } Z < 0
\end{cases} \]  

(8)

In the above relation, the value of $Z$ can be estimated as (Kahya & Kalayci 2004)

\[ Z = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \text{sign}(x_j - x_k) = \begin{cases} 
+1 & \text{if } (x_j - x_k) > 0 \\
0 & \text{if } (x_j - x_k) = 0 \\
-1 & \text{if } (x_j - x_k) < 0
\end{cases} \]  

(9)
The increasing or decreasing trend in $x_t$ is identified based on $Z_c$’s calculated values at a 5% significance level (greater than 0 and $-1.96 \geq Z_c \geq 1.96$) on $n_t$ (lag-1 autocorrelation). The magnitude of the trend was identified using Sen’s (Sen 1968) method (Adarsh & Janga Reddy 2015).

The change point of the trend was analyzed using the sequential Mann–Kendall (SQM-K) test (Liu et al. 2008; Sonali & Nagesh Kumar 2013; Sayemuzzaman & Jha 2014; Jones et al. 2015). The SQM-K is a sequential progressive $S_q(t)$ and backward $S_{q'}(t)$ analysis of the MK test. In this case, sequential progressive $S_q(t)$ and backward $S_{q'}(t)$ series intersect or diverge from each other for an extended period. The beginning of the year of divergence exhibits the $T_{AC}$. In $S_q(t)$ analysis, the number of cases $X_j$ ($j = 1, 2, 3 \ldots n$) $> X_k$ ($k = 1, 2 \ldots j - 1$), denoted by $n_t$, is counted at each comparison. In $S_{q'}(t)$ estimation, the number of times, $N_t$ for which $X_j > X_k$ was counted. The sequential test statistics $S_t$ are calculated by

$$S_t = \sum_{i=1}^{n} N_t$$  \hspace{1cm} (10)

The mean and variance of the test statistics are calculated as follows

$$E(S) = \frac{n(n - 1)}{4}$$  \hspace{1cm} (11)

$$\text{Var}(S_t) = \frac{j(j - 1)(2j + 5)}{72}$$  \hspace{1cm} (12)

The $S_q(t)$ is estimated as,

$$S_q(t) = \frac{S_t - E(S)}{\sqrt{\text{Var}(S_t)}}$$  \hspace{1cm} (13)

The $S_{q'}(t)$ was determined, estimated similarly, with $x_t$’s termination point being the beginning.

**Detrending of CPs**

The linear detrended data series is obtained by eliminating the original data series linear trend each year. The original data series value is added to the detrended data series to maintain a close variation range to the original data.

In the present study, the nonlinear detrending of the various CPs was performed using the CEEMDAN technique (Antico et al. 2014). The CEEMDAN technique of signal processing decomposes the input data to intrinsic mode functions (IMFs) with varying phase and amplitude and residuals (trend). An IMF is a continuous map, which fulfills the following condition (Huang et al. 1998): (a) the number of zero intersections and the extrema must be equivalent or have a difference limited to one, (b) the mean estimation of the upper envelope framed by local maxima and lower envelope shaped by lower minima must be equivalent to zero at any point. Within this condition of IMF, the decomposition procedure of CEEMDAN is given below:

1. Show the input signal, $x(t)$.
2. Identify the local maxima and minima of time series.
3. Calculate both upper and lower envelopes by joining all local maxima using any suitable signal decomposition method, such as cubic splines.
4. Calculate the local average value ($m_1(t)$) between both upper and lower envelopes.
5. The first component is calculated as $h_1(t) = x(t) - m_1(t)$.

If the first component (as computed in step 5) does not fulfill the IMF’s conditions, repeat step 2 to step 5 by considering $h_1(t)$ as the next input signal. This procedure is repeated for $k$ times until it fulfills the IMF conditions i.e., $h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t)$, then $c_1(t) = h_{1k}(t)$ is considered as the first IMF. Then residue $r_1$ is determined by subtracting the first IMF from $x(t)$ (i.e., $r_1(t) = x(t) - c_1(t)$). Continue this procedure for $r_1$ until series $r_1(t)$ becomes a monotonic function such that the extraction of further IMF is not possible. Therefore, signal $x(t)$
can be illustrated as:

\[ x(t) = \sum_{i=1}^{l-1} c_i(t) + \eta(t) \]  

(14)

The CEEMDAN method works by adding different realization of white noise to an original time series to obtain a series \( x_i(t) = x(t) + w_i(t) \), where \( w_i(t) \) are the white realization and then decomposing it via the EMD method. Procured from the first series \( x_i(t) \), one can compute the first series component \( x(t) \) as

\[ c^{-1}(t) = \frac{1}{l} \sum_{i=1}^{l} c_i^{(1)}(t) \]  

(15)

The first residue is computed as

\[ r^1(t) = x(t) - c^{-1}(t) \]  

(16)

Moreover, then, \( c^{-1}(t) \) is calculated as the average of the individual series of the implementation of \( r^1(t) \) series along with the first component of EMD white noise decomposition \( w_i(t) \).

The CEEMDAN was preferred for obtaining the nonlinearly detrended data series using the ‘Rlibeemd’ package (Luukko et al. 2016) of R software in the present study. The original data of various CPs (\( T_{\text{max}}, T_{\text{min}}, R_{\text{Hmax}}, R_{\text{Hmin}}, \text{SSH} \)) are imported into the software. With the help of the Rlibeemd package, CEEMDAN decomposes the input data to IMFs and a residual series.

**Scenarios of ET\(_0\) estimated using the detrended CPs**

In the present study, the main objective is to compare the effects of linear and nonlinear detrending (i) between different temperature factors (\( T_{\text{max}}, T_{\text{min}} \)) and (ii) non-temperature factors (i.e., \( R_{\text{Hmax}}, R_{\text{Hmin}}, \text{SSH} \)) on changing ET\(_0\). The number of total combinations created was 23, including the original scenario CP1. The original scenario CP1 is estimated from the observed CPs, and two other groups (i.e., linear and nonlinear) are created. Both the scenarios contain 11 different combinations of recalculated ET\(_0\) using various sets, as shown in Table 2 of the observed and detrended CPs.

Single or multi CPs were detrended from Group 1, consisting of a linear trend, and Group 2 of nonlinear trends. The detrended CPs with other observed CPs were utilized for the re-estimation of ET\(_0\). A total of 23 combinations of ET\(_0\), including the original set CP1, CP2 to CP11 in Group 1, and CP2 to CP11 in Group 2, are applied. In the combination CP2 to CP4, the influences of detrending one or more temperature factors are contrasted gradually, i.e., in CP2, \( T_{\text{max}} \) is detrended, CP3 \( T_{\text{min}} \) is detrended, CP4 both \( T_{\text{max}} \) and \( T_{\text{min}} \) are detrended. At the same time, in CP5 to CP11, the influences of detrending one or more non-temperature factors CP5 to CP10 are non-temperature factors, i.e., in CP5 \( R_{\text{Hmax}} \) is detrended, CP6 \( R_{\text{Hmin}} \) is detrended, CP7 both \( R_{\text{Hmax}} \) and \( R_{\text{Hmin}} \) are detrended, CP8 SSH is detrended, CP9 SSH and \( R_{\text{Hmax}} \) are detrended, CP10 SSH and \( R_{\text{Hmin}} \) are detrended, in CP11 SSH, \( R_{\text{Hmax}} \) and \( R_{\text{Hmin}} \) are detrended. In CP12, all the observed CPs are detrended.

**Table 2** | Combinations de-trended CPs in the predefined 12 scenarios

<table>
<thead>
<tr>
<th>Climatic parameters</th>
<th>Scenarios/ Combinations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CP1</td>
</tr>
<tr>
<td>( T_{\text{max}} ) (°C)</td>
<td>*</td>
</tr>
<tr>
<td>( T_{\text{min}} ) (°C)</td>
<td>*</td>
</tr>
<tr>
<td>( R_{\text{Hmax}} ) (%)</td>
<td>*</td>
</tr>
<tr>
<td>( R_{\text{Hmin}} ) (%)</td>
<td>*</td>
</tr>
<tr>
<td>SSH (h)</td>
<td>*</td>
</tr>
</tbody>
</table>

*Climatic parameter de-trended in the scenario and used for re-estimating ET\(_0\).*
effect level between temperature and non-temperature parameters could be shown by comparing scenarios (CP2 to CP4) with scenarios (CP5 to CP11) (Table 2).

**RESULTS**

Trend analysis and comparison between Sen’s slope (b) and regression slope

In the Mann–Kendall test, parameters like modified Mann–Kendall Statistics (Zc) and Sen’s slope (b) were assigned to distinguish the increasing or decreasing trends in the climatic time series parameters. From Table 3, it is clear that at a 5% level of significance, the estimated Zc value predicts a significant increasing trend for Tmin. In contrast, a significant decreasing trend was observed for sunshine duration and evapotranspiration. The remaining CPs show an insignificant increasing trend at a 5% level of significance (Table 3).

The results obtained for abrupt change year (TAC) are also presented in Table 3. The TAC for Tmax, RHmax, and RHmin was observed in 1985, 1983, and 1982, respectively. However, for Tmin, SSH, and ETo, TAC was not observed as the two series, Sd (t) and Sd0 (t) did not cross each other. The Sen’s slope b for ET0 and 5 CPs vary to a small degree. The magnitude of positive Sen’s slope follows a sequence of Tmin > RHmin > RHmax > Tmax that the mean rate of increase of Tmin per year is maximum for the studied parameters. In contrast, the rate of increase of Tmax is the lowest of the studied parameters. However, for sunshine duration and evapotranspiration, the value of the Sen slope (b) is negative. Total sunshine duration decreases at a rate of 0.049 h per year, and evapotranspiration decreases at a rate of 0.078 mm d\(^{-1}\) per year. This helps to determine the most critical parameter responsible for negative trends in ET0. The same table also depicts that the magnitude of Sen slope (b) and the regression slope (RS) of related CPs are close. Although Sen slope (b) detector is nonparametric and the RS technique is a parametric technique, both the techniques are linear. Therefore, a minor difference in the b and RS values gives very similar results for analyzing the detrending impacts on reference evapotranspiration and verified the correctness of using RS values for detrending.

Temporal changes of CPs and ET0 and their trends

Temporal changes in annual CPs and their linear trends and nonlinear trends during the study period 1980–2015 are shown in Figure 2(a)–(f). Figure 2(a) shows that the linear and nonlinear trend lines are separate until the nonlinear line decreases and meets the linear range. The linear trend line of Tmax is similar to the nonlinear trend from 1996 onwards until 2015. Before 1996, nonlinear trends are on a higher side than the linear trend. The significant increasing linear trend of Tmin (Figure 2(b)) is different from the significant increasing nonlinear trends except in 1986–1988 and 2006–2008. The fluctuation patterns of RHmax (Figure 2(c)) and RHmin (Figure 2(d)) were generally similar. However, the magnitude of fluctuation in RHmin was more than the RHmax. In RHmax and RHmin trends, there was a weak increase from 1980–2015. For RHmax, both linear and nonlinear trends differed insignificantly (the linear trend is minute differing from the nonlinear trend) except in 1986–1991 and 2010–2012. For RHmin, the linear trend was generally different from the nonlinear trend except in 1987 and 2001, where the nonlinear trend increased and decreased back, respectively. For the SSH (Figure 2(e)), both the linear and nonlinear trends sharply decreased from 1980–2015. The linear trend was generally different from nonlinear trends throughout the study period except in 1988 and 2004–2005. From the nonlinear trends, SSH seems to decrease, and the nonlinear variation of SSH adds to the nonlinear change of ET0. These major or

<table>
<thead>
<tr>
<th>CPs</th>
<th>Zc</th>
<th>b</th>
<th>Regression slope</th>
<th>TAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tmax (°C)</td>
<td>1.24</td>
<td>0.006 (°C per year)</td>
<td>0.0044 (°C per year)</td>
<td>1985</td>
</tr>
<tr>
<td>Tmin (°C)</td>
<td>3.95**</td>
<td>0.095 (°C per year)</td>
<td>0.0978 (°C per year)</td>
<td>–</td>
</tr>
<tr>
<td>RHmax (%)</td>
<td>0.34</td>
<td>0.031 (% per year)</td>
<td>0.0214 (% per year)</td>
<td>1983</td>
</tr>
<tr>
<td>RHmin (%)</td>
<td>0.4</td>
<td>0.013 (% per year)</td>
<td>0.021 (% per year)</td>
<td>1982</td>
</tr>
<tr>
<td>SSH (h)</td>
<td>–5.65**</td>
<td>–0.049 (h per year)</td>
<td>–0.052 (h per year)</td>
<td>–</td>
</tr>
<tr>
<td>ETo (mm d(^{-1}))</td>
<td>–4.57**</td>
<td>–0.0078 (mm d(^{-1}) per year)</td>
<td>–0.0078 (mm d(^{-1}) per year)</td>
<td>–</td>
</tr>
</tbody>
</table>

Zc, MMK statistic; b, Sen’s slope; TAC, abrupt change year; ** significant trend at 5% significance level.
minor differences in linear and nonlinear trends in basic input parameters for ET₀ estimation create a difference in recalculated ET₀ after linear and nonlinear detrending.

The distinct variations of the five principal CPs resulted in a difference of ET₀. The ET₀ variation (Figure 2(f)) and its linear and nonlinear trend represented a decreased trend. The significant difference between the linear and nonlinear trends in ET₀ contributes to the difference in regenerated ET₀ between Group 1 and 2.

**Impact of removing linear trends from annual CPs on ET₀**

In this analysis, the ET₀ was recalculated using the linearly detrended CPs (Table 2) from Group 1 (linearly detrended) throughout the study period, i.e., from 1980 to 2015, and compared the recalculated ET₀ with the original calculated ET₀ under Scenario 1 (CP1).

For CP2, as depicted in Figure 3(a), the recalculated ET₀ values obtained after detrending the $T_{\text{max}}$ are lower throughout the study years except in 1997, where the recalculated value is higher than the CP1 value. The results of the study showed that although the $T_{\text{max}}$ is insignificantly increasing during the study period, the ET₀ value decreased. For CP3, the recalculated ET₀ values obtained after detrending the $T_{\min}$ are higher during 1980–1983, 1986–1988; from 1993 to 2010, the detrended ET₀ is slightly lower than the CP1 ET₀ (Figure 3(b)), and from 2011 to 2015, the detrended ET₀ is the same as CP1 ET₀. However, $T_{\min}$ is significantly increased during the study period but detrending of $T_{\min}$ did not affect the ET₀ values. Comparing CP4 and CP1 (Figure 3(c)) shows the decreasing values of ET₀. The recalculated ET₀ values are higher during 1981–1982 and in 1997. Overall, the detrended ET₀ is lower than the CP1 ET₀.

The findings of the study showed that although $T_{\text{max}}$ and $T_{\min}$ have been increased during the study period, however, detrending both $T_{\text{max}}$ and $T_{\min}$ resulted in a decrease in the ET₀ value. Thus, it may be concluded that detrending of $T_{\text{max}}$ and $T_{\min}$ has a negative effect on ET₀. Thus, for temperature parameters, except for scenario CP3 ($T_{\min}$ de-trended), the recalculated ET₀ was below the ET₀ curve of CP1, which concludes that detrending T factors (CP2, CP3, CP4) result in decreasing ET₀.

Detrending RH parameters (CP5 to CP7), as depicted in (Figure 3(d)–(f)), showed a slight increase in ET₀ in all three cases. Hence, an insignificant increase in both RHₘₐₓ and RHₘᵟₐᵦ did not affect the decreasing trend of ET₀.
Overall, the significant decreasing trend of sunshine duration (CP8) explains the decreasing trend of evapotranspiration (Figure 3(g)). After 2002, the recalculated ET₀ is higher than that estimated in scenario CP1. Detrending of sunshine duration counters the detrending effect of humidity factors CP9, CP10, and CP11, or we can conclude that the effect of the significantly decreasing sunshine duration decreasing ET₀ values is much stronger than an insignificant increase in RH factors (Figure 3(h)–(j)).

Variation in ET₀ for CP1 and CP12 (detrending all the CPs) is similar to that obtained by detrending sunshine duration and RH (CP11) (Figure 3(k)). The result shows that with the decreasing trend in sunshine duration the decreasing trend in ET₀ is much stronger than an insignificant increase in T_max and a significant increase in T_min.

Impact of removing nonlinear trends from annual CPs on ET₀

For nonlinear detrending, CP2 insignificantly affects the variation in ET₀ during the study period (Figure 4(a)). Analysis of Figure 4(a) revealed that the original ET₀ and the values of recalculated ET₀ of CP3 show decreasing

Figure 3 | Variations of annual original ET₀ (CP1) and linearly de-trended CPs (a–k) ET₀ over 1980–2015.

Figure 4 | Variations of annual original ET₀ (CP1) and nonlinearly de-trended CPs (a–k) ET₀ over 1980–2015.
values of ET₀ for both the scenarios. The estimates of recalculated ET₀ for CP3 (Figure 4(b)) are the same as the CP1 from 1985 onwards except for 1981–1982 and 1983. The results show that although the Tₘᵢₙ is significantly increased during the study period, detrending the Tₘᵢₙ did not affect ET₀. A similar insignificant impact was observed for CP4 (Figure 4(c)). The detrending of both the Tₘₐₓ and Tₘᵢₙ has a negligible effect on ET₀. The increasing trend of RHₘₐₓ and RHₘᵢₙ has an insignificant effect on ET₀ after nonlinear detrending CP5, CP6, and CP7 (Figure 4(d)–(f)). The findings of the study revealed that the detrending of RHₘₐₓ and RHₘᵢₙ has an insignificant effect on ET₀. However, the impact of decreasing sunshine duration CP8 (Figure 4(g)) on reducing ET₀ is much more substantial than an insignificant increase in RH factors, which is similar to linear detrending. The ET₀ curve of CP12 (Figure 4(h)) increased as CP8, CP9, and CP10 (Figure 4(g)–(i)) when compared with CP1. Thus, in the annual series, for both the linear and nonlinear detrending, sunshine duration is the dominant climatic parameter to explain the decreasing trend of ET₀ in the region. Hence, we can conclude that the detrending sunshine hour surpasses the detrending of other selected CPs.

Impact of detrending all the CPs on ET₀

The original ET₀ (CP1) was compared with scenario CP12 of both Group 1 and Group 2 to know the effect of detrending if all the CPs were detrended. Thus obtained, the results are presented in Table 4 and Figure 5 (for both Group 1 and Group 2). From Table 4, it is clear that the trend and intercept obtained by linear regression were similar for both original ET₀ and nonlinearly detrended ET₀ for scenario CP12, whereas, trend and intercept for linearly detrended ET₀ was not identical to the other two scenarios. However, the nature of the trend was decreasing in all the scenarios (Figure 5). Findings support that the linear detrending of CPs significantly influences ET₀ compared to nonlinear detrending. However, the results obtained by nonlinear detrending are more convincing than linear detrending based on the analysis of trend and intercept (Table 4).

Except for scenario CP12, there is no other scenario that combines the temperature and non-temperature factors because the results from the present study show that (i) the impact of detrending two temperature factors on declining ET₀ is most significant when compared with the effect of detrending single temperature factors. Furthermore, the effect of detrending Tₘₐₓ and SSH as a single parameter was more significant than detrending RH factors and Tₘᵢₙ which accentuate the critical roles of Tₘₐₓ and SSH on the varying ET₀ as an individual factor. Therefore, it is not required to add more scenarios to illustrate the impacts of the detrending of combined RHₘₐₓ, RHₘᵢₙ, and Tₘᵢₙ because their impacts will be small. Therefore, CP12, which contains CPs of temperature and non-temperature factors, would thoroughly illustrate the effects of detrending CPs on ET₀.

![Figure 5](http://iwaponline.com/jwcc/)

**Figure 5** | Variation of annual ET₀ for CP1, CP12 for the Group 1 and CP 12 for Group 2 over 1980 to 2015.

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Comparison among CP1, and de-trended CP12 (linear and nonlinear)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S No</td>
<td>Scenarios</td>
</tr>
<tr>
<td>1</td>
<td>CP1 (original ET₀)</td>
</tr>
<tr>
<td>2</td>
<td>CP12 (linear de-trended)</td>
</tr>
<tr>
<td>3</td>
<td>CP12 (nonlinear de-trended)</td>
</tr>
</tbody>
</table>
ΔET₀ variations under different scenarios

ΔET₀ is the difference in the original ET₀ and the recalculated ET₀ in which one or multiple CPs (different scenarios) have been de-trended linearly or nonlinearly. The difference is estimated for Group 1 (linearly detrended) and Group 2 (nonlinearly detrended). Figure 6(a) represents the variations of ΔET₀, in which values of ET₀ were re-computed using linearly and nonlinearly detrended Tₘₐₓ (CP2). The total absolute ΔET₀ for CP2 is 3.19 mm d⁻¹, and that for nonlinear detrending is 0.6 mm d⁻¹ (Table 5). Similarly, Figure 6(b,c) represents both sets of detrending considering CP3 (Tₘᵢₙ) and CP4 (Tₘₐₓ and Tₘᵢₙ) scenarios. Linear detrending ΔET₀ values of temperature factors are more substantial than those of nonlinear detrending ΔET₀ as shown in Table 5. In both the detrending methods, detrending Tₘᵢₙ has the least influence on ET₀, followed by Tₘₐₓ’s detrending and combining the two temperature factors. Similarly, the linear and nonlinear detrending for scenarios (CP5–CP7) showed similar trends, i.e., the ΔET₀ values in both the cases are higher for scenarios CP6 and CP7 compared to scenario CP5 (Figure 6(d)–(f)). For linear detrending, the total absolute linear detrending differencing decreased from CP7 (3.47 mm d⁻¹) > CP6 (2.88 mm d⁻¹) > CP5 (0.77 mm d⁻¹) and for nonlinear detrending, total absolute linear detrending differencing decreased from CP6 (1.09 mm d⁻¹) > CP7 (0.99 mm d⁻¹) > CP5 (0.41 mm d⁻¹). The analysis also concludes that scenarios CP6 and CP7 have a similar influence on ET₀ on detrending; these will increase the value of ET₀ significantly for both the groups. In contrast, in the case of CP5, the average estimates of ΔET₀ move near to zero. Hence detrending RHₘₐₓ has the least influence on ET₀. For the ΔET₀ variations of Group 1 and Group 2 for scenarios CP8 to CP11, the pattern of detrending is the same, i.e., the ΔET₀ values for scenario CP8 and CP9, and CP10 and CP11 showed the same pattern, and

Figure 6 | ΔET₀ variation due to respective CPs for Group 1, and Group 2 over 1980–2015.
similar to \( \Delta ET_0 \) values (Figure 6(g)–(j)). For linear detrending, total absolute linear detrending differencing decreased from CP11 (4.9 mm d\(^{-1}\)) > CP10 (4.85 mm d\(^{-1}\)) > CP9 (4.8 mm d\(^{-1}\)) > CP8 (4.62 mm d\(^{-1}\)). The same pattern was observed for nonlinear detrending, where total absolute differencing decreased from CP11 (1.6 mm d\(^{-1}\)) > CP10 (1.58 mm d\(^{-1}\)) > CP9 (1.55 mm d\(^{-1}\)) > CP8 (1.45 mm d\(^{-1}\)).

The value for absolute \( \Delta ET_0 \) is significantly higher for linear detrending than nonlinear detrending in all the cases. Hence, the influence of linear detrending is more significant than that of nonlinear detrending. From the analysis, it may be concluded that \( T_{\text{min}} \) (CP3) and RH\(_{\text{max}}\) (CP5) have the least influence on \( ET_0 \), whereas the most influencing independent climatic parameter was Sunshine duration (CP8).

**\( \Delta ET_0 \) variations of Group 1 and Group 2 for scenario CP12**

In both the linear and nonlinear detrending, the detrending pattern is the same for scenario CP12 (Figure 7). The maximum and minimum value of \( \Delta ET_0 \) for linear detrending was observed as 0.37 and −0.24 mm d\(^{-1}\) in 1988 and 2011. In nonlinear detrending, 0.18 mm d\(^{-1}\) was the maximum \( \Delta ET_0 \) in 1999, and −0.08 mm d\(^{-1}\) was the minimum value observed in the years 2004 and 2011. Total absolute linear detrending differencing for both linear and nonlinear detrending is 4.12 and 1.77 mm d\(^{-1}\), respectively (Table 5).

Different statistical properties of \( \Delta ET_0 \) like maximum, minimum, and average \( \Delta ET_0 \) are represented in Figure 8. The \( \Delta ET_0 \) statistic for Group 1 is significantly higher than Group 2, which may be because meteorological data follow a nonlinear pattern. Hence, nonlinear detrended \( ET_0 \) is closer to actual \( ET_0 \) which resulted in the lowest \( \Delta ET_0 \) values. Therefore, it may be proposed that nonlinear detrending gives closer results to the benchmark \( ET_0 \) values than linear detrending. In all the \( \Delta ET_0 \) analyses, it is concluded that a significant difference was observed in all the CPs scenarios. For linear detrending, \( \Delta ET_0 \) values in all the cases are on the higher side. The similar values of \( \Delta ET_0 \) were found on the lower side in the case of nonlinear detrending.

**Table 5** Statistical properties of \( \Delta ET_0 \) for CP2 to CP12 in Group 1 and Group 2

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Group 1</th>
<th></th>
<th>Group 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max (mm d(^{-1}))</td>
<td>Min (mm d(^{-1}))</td>
<td>Abs. Sum (mm d(^{-1}))</td>
<td>Mean (mm d(^{-1}))</td>
</tr>
<tr>
<td>CP2</td>
<td>0.21</td>
<td>−0.05</td>
<td>3.19</td>
<td>0.09</td>
</tr>
<tr>
<td>CP3</td>
<td>0.06</td>
<td>−0.14</td>
<td>1.07</td>
<td>0.03</td>
</tr>
<tr>
<td>CP4</td>
<td>0.25</td>
<td>−0.07</td>
<td>3.37</td>
<td>0.09</td>
</tr>
<tr>
<td>CP5</td>
<td>0.08</td>
<td>−0.06</td>
<td>0.77</td>
<td>0.02</td>
</tr>
<tr>
<td>CP6</td>
<td>0.15</td>
<td>−0.24</td>
<td>2.88</td>
<td>0.08</td>
</tr>
<tr>
<td>CP7</td>
<td>0.37</td>
<td>−0.18</td>
<td>3.47</td>
<td>0.10</td>
</tr>
<tr>
<td>CP8</td>
<td>0.26</td>
<td>−0.32</td>
<td>4.62</td>
<td>0.13</td>
</tr>
<tr>
<td>CP9</td>
<td>0.32</td>
<td>−0.33</td>
<td>4.80</td>
<td>0.13</td>
</tr>
<tr>
<td>CP10</td>
<td>0.31</td>
<td>−0.30</td>
<td>4.85</td>
<td>0.13</td>
</tr>
<tr>
<td>CP11</td>
<td>0.29</td>
<td>−0.32</td>
<td>4.90</td>
<td>0.14</td>
</tr>
<tr>
<td>CP12</td>
<td>0.37</td>
<td>−0.24</td>
<td>4.12</td>
<td>0.11</td>
</tr>
</tbody>
</table>

**Figure 7** \( \Delta ET_0 \) variation due to CP12 for Group 1, and Group 2 over 1980–2015.
DISCUSSION

Most CPs are stochastic and generally have non-normal distribution. Therefore, the application of linear detrending may be unable to capture trends correctly. Table 3 depicts the comparison between the linear RS ($S$) and Sen’s slope ($b$) values of all the selected CPs, which helps to understand the similarity or differences between linear and nonlinear trending.

The results showed that the deviation between $S$ and $b$ values for CPs was small. Even though Sen’s slope method is nonparametric and the linear RS method a parametric technique, the two approaches are linear. In this way, the slight dissimilarities between $S$ and $b$ estimates would prompt a very close outcome for examining detrending impacts on ET$_0$ and affirmed the appropriateness of utilizing $S$ values to detrend CPs.

The scenario 12 (CP12) is the only case that combines both temperature and non-temperature parameters mainly because simultaneously detrending the temperature parameters ($T_{\text{max}}$ and $T_{\text{min}}$) on declining ET$_0$ were the biggest when contrasted with the effects of detrending of single parameters. Furthermore, the effects of detrending SSH on decreasing ET$_0$ were much more significant than the detrending of temperature, RH parameters in all three cases (i.e., $RH_{\text{max}}$ and $RH_{\text{min}}$), which highlighted that sunshine duration (SSH) plays the most vital role in decreasing ET$_0$ in the eastern Himalayan region.

The decreasing trend in ET$_0$ identified in this study is concurrent with many studies in India and worldwide. Pandey et al. (2016) concluded that SSH is the main factor driving the ET$_0$ process in Northeast India. Poddar et al. (2018), in a study on the humid environment in the western Himalayan region of India, reported that solar radiation and temperature are the crucial factors to control ET$_0$. Jhajharia & Singh (2011) stated that the decrease in SSH has a positive relationship with the diurnal temperature range (DTR) and evaporation, leading to a reduction in evapotranspiration in Northeast India. Goroshi et al. (2017), in a study of evapotranspiration over India, also reported a decreasing trend in ET$_0$ over northeast India. Patle et al. (2019), using sensitivity analysis for Gangtok, East Sikkim, concluded that ET$_0$ changes positively related to SSH and T factors. According to Li et al. (2014), one of the main reasons behind the decreasing trend of ET$_0$ in northwestern China is a decrease in DTR. All these studies generally agree that the SSH is the most influential parameter in modeling the evapotranspiration process, especially in the humid climate. The conclusion of our study of the original and re-estimated ET$_0$ found in both cases (linear and nonlinear detrended) CPs also similar to the studies mentioned above.

By relating the influence of eliminating trends (linear and nonlinear) from the CPs on ET$_0$ in Sikkim, dissimilarities were found for the recalculated ET$_0$ between Group 1 and Group 2 scenarios. Due to the seasonal periodicity in the CPs, including ET$_0$, the results from Group 2 were even more conclusive for assessing the impacts of global warming and climate change on ET$_0$.

The decrease of ET$_0$ results in reduced crop water/irrigation requirements for crops and plants in the region. Diminished ET$_0$ would bring about increased overland flow. Accordingly, it may increase the flood risk due to accelerated snowmelt on the alpine zone in the summer season, resulted from increased temperature. Therefore, the region’s wetter conditions under the present global warming scenarios and drier are subsequently detrending the CPs and re-evaluating dry spell conditions.
CONCLUSIONS

This study aims to identify the impacts of eliminating trends (linear and nonlinear) from the meteorological parameters (CPs) that drive \( \text{ET}_0 \) processes. Accordingly, 23 scenarios, including the non-de-trended \( \text{ET}_0 \) (CP1), and Group 1 (by eliminating linear trend from CPs) and Group 2 (by eliminating nonlinear pattern from CPs), were set to know how the CPs influenced \( \text{ET}_0 \) for the period 1980–2015 in Gangtok, East Sikkim. To study the influence of trend, the \( \text{ET}_0 \) was re-estimated after detrending the respective CPs and then compared with non-de-trended \( \text{ET}_0 \) (CP1). The main conclusions derived are as follows:

1. The difference between \( \text{ET}_0 \) and the detrended \( \text{ET}_0 \) (\( \Delta \text{ET}_0 \)) was significantly higher for linear detrending (Group 1) as compared to nonlinear detrending (Group 2). For linear detrending, the maximum difference \( \Delta \text{ET}_0 \) was observed as 0.37 mm d\(^{-1}\) for CP 7 and CP 12 scenario, and the minimum difference was observed as –0.05 mm d\(^{-1}\) for CP 2.

2. In both the groups, the consistent mean difference of \( \Delta \text{ET}_0 \) was observed for CP 8 to CP 12 when sunshine duration and RH parameters were detrended. However, results from Group 2 were reasonable and conclusive as the Group 2 results were closer to those of the \( \text{ET}_0 \). The nonlinear detrending gives closer results to the original as compared to linear detrending.

3. The SSH was the most crucial parameter affected because there was the highest increase in \( \text{ET}_0 \) when SSH was detrended either in Group 1 linearly or nonlinearly in Group 2. A decline in SSH and \( T_{\text{max}} \) caused a general reduction of \( \text{ET}_0 \), which neutralized increased \( T_{\text{min}} \) and RH on \( \text{ET}_0 \).

4. The declines of \( T_{\text{max}} \) and increment of RH likewise added to the low abatement of \( \text{ET}_0 \). Overall, the combined impacts of all CPs caused the general decline of \( \text{ET}_0 \).

5. Additionally, the comparison of removing trends nonlinearly from single or multiple CPs may be useful to understand the changing pattern of \( \text{ET}_0 \) under global warming conditions.

AUTHOR’S CONTRIBUTION STATEMENT

Vanita Pandey studied the conception and design, acquisition of data and drafted the manuscript. Indira Taloh analysed and interpreted the data. P. K. Pandey edited and made critical revisions. All authors of this paper have directly participated in the writing, editing, planning, execution, and analysis of this study.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

REFERENCES


Verma, I. J., Jadhav, V. N. & Erande, R. S. 2008 Recent variations and trends in potential evapotranspiration (PET) over India. *MAUSAM* 59 (1), 119–128.


First received 2 June 2020; accepted in revised form 12 May 2021. Available online 12 June 2021