Grid-scale evaluation of five reference evapotranspiration methods based on the climate forecast system reanalysis data

Tekalegn Ayele Woldesenbet[1], Nadir Ahmed Elagib[2]

[1]Ethiopian Institute of Water Resources, Addis Ababa University, P.O. Box. 150461, Addis Ababa, Ethiopia.

[2]Böckingstr. 55, Köln Mülheim 51063, Cologne, Germany.

e-mail address: tekalegnay@yahoo.com; tekalegn.ayele@aau.edu.et

***** Correspondence: tekalegnay@yahoo.com; Tel.: +251944055445

Abstract

Climate Forecast System Reanalysis data offer a promising database for overcoming the limitations in availability and reliability of climatological data and, hence, for understanding the hydrological processes. Using these data on grid-by-grid, seasonal and yearly scales, the present study attempts to advance the spatiotemporal evaluation of two radiation-based (Priestley–Taylor and Makkink) and three temperature-based (Hargreaves–Samani, Thornthwaite and Blaney–Criddle), against estimates of grass reference evapotranspiration (ETo) by FAO Penman-Monteith method (FAO-PM). The analysis was performed for the period 1979–2013, considering the second largest (79,000 km^2) river system in Ethiopia, i.e. Omo-Gibe basin, which accommodates national parks and vast hydropower, cultivation and afforestation developments and discharges its flow to Lake Turkan in Kenya. To comprehensively explain the pattern of PET, the influences of temperatures, rainfall, wind speed, radiation, relative humidity and elevation on PET were also examined. The results emphasize the outperformance of Hargreaves-Samani method. In overall, both the annual and seasonal FAO-PM estimates are captured by this method for most of the grid locations. Annual trends in ETo in the upper region increased but rainfall trends decreased. These trends might negatively impact the rain-fed food production by reducing soil moisture availability in the river basin. Comparatively, trends in rainfall in the middle and lower regions increased with a higher magnitude while ETo increased with a smaller magnitude compared. The above-mentioned trends in ETo are attributable to rising temperature and decreasing relative humidity, wind speed, and solar radiation, respectively. If these trends would continue, we would expect increase in soil moisture for sugarcane plantation in the middle and lower region and attenuation of water loss from reservoirs in the river basin. This study improves the understanding of the best potential evapotranspiration methods in similar data-scarce river basins in Ethiopia or other transboundary rivers in the region or worldwide.

Keywords: Trend analysis; FAO Penman–Monteith; radiation-based methods; temperature-based methods; Omo-Gibe river basin; NCEP CFSR data

1. Introduction

Evapotranspiration plays a vital role in connecting the terrestrial and atmospheric component of the climate system through moisture and energy exchange. It is a vital hydroclimatic parameter connecting environment, carbon-climate feedbacks, and water resources development and management (Fisher et al. 2017). Hydrological modeling, water resources management, irrigation management and environmental assessment need accurate estimates of evapotranspiration (Khoob, 2008; Lang et al. 2017). As it is difficult to measure actual evapotranspiration (AET) under field condition, it is usually calculated relative to potential evapotranspiration (Ding et al. 2013; Jung et al. 2016). Potential evapotranspiration (PET) is vital to quantify the atmospheric demand for water of a river basin. Therefore, PET could be used for irrigation water management, drought assessment, and understanding impacts of climate variability. PET has also been extensively used in the estimation of AET using various remote sensing-based models (Senay et al. 2007; Maeda et al. 2011; Wagle et al. 2017). As an input in various water balance model, PET could also be used in assessing AET of a catchment.

Since many methods have been introduced for estimating PET, the choice of the best one is challenging and governed by availability of the observed climate data. Several studies compared and evaluated various PET estimation methods (Lu et al. 2005; Tabari, 2010; Djaman et al. 2015; Song et al. 2019). Bogawski and Bednorz (2014) developed a simple relationship between PET candidate approaches and FAO Penman-Monteith (FAO-PM) and its modified approaches. Depending on its physiological and aerodynamic notions, the FAO-PM was recommended by the Food and Agriculture Organization (FAO) and World Meteorological Organization (WMO) as the standard grass reference evapotranspiration (ETo) method (Allen et al. 1998). As a standard method, FAO-PM can be used worldwide in many regions without the need for extra modifications of parameters (Allen et al. 2005; Raziei and Pereira, 2013; Djaman et al. 2015; Song et al. 2019). Its utility is however limited in data-scare regions because it requires many meteorological inputs. It is costly to equip meteorological stations to observe the full range of climatic elements, including for example solar radiation, wind speed, and relative humidity in developing countries. Other simple and effective methods, which need only readily available meteorological data observed on ground, were therefore developed to evaluate PET or ETo. Assessing the performance of these simple approaches is however vital for choosing the suitable ones in accordance to climatic region and availability of climate data. Various estimation approaches perform differently in agro-climatic zones (Tabari, 2010; Rahimikhoob et al. 2012; Song et al. 2019).

Many scientists have narrated the key gaps in climate services and data in Africa and the need for bridging these gaps (Washington et al. 2006; Dinku et al. 2014; Nordling, 2019). Ethiopia is no exception among the African countries whose district-level planning and development potentials are hampered by such gaps (Woldesenbet et al. 2017; Dinku et al. 2018). Climate variability in the Omo-Gibe basin results in frequent droughts. Accurate estimates of PET are important in drought monitoring and forecasts in southern Ethiopia. The Omo-Gibe river basin is one of the most crucial river basins in Ethiopia in terms of water resources development and climate change impacts. Studies assessing the performance of different PET equations are rare in the literature for Omo-Gibe river basin.

Moreover, there is no study dedicated to the analysis of trends in PET nor in its most influential input climate variables. Therefore, the objectives of this paper are threefold. Firstly, five simple PET methods are compared with the standard combination method of FAO-PM in the Omo-Gibe river basin. The candidate PET estimation methods are temperature-based

(Thornthwaite: TW, Hargreaves-Samani: HS and Blaney-Criddle: BC), radiation methods (Priestley–Taylor: PT and Makkink: MK). Secondly, trend analysis for both PET estimates and input climatic variables are investigated. Thirdly, the most influential climatic variables in changing the PET are identified. To this end, the analysis utilized Climate Forecast System Reanalysis (CFSR) data of the National Centers for Environmental Prediction (NCEP). Unlike most common practices, the present study put emphasis on performing the analysis on grid, annual and seasonal bases.

2. Study Area

The Omo-Gibe River and its tributaries is one of the twelve river basins in Ethiopia (Figure 1). It has an area of around 79,000 km^2. It is located from 6°25’ N to 9°24’ N latitude and from 35°36’ E to 38°34’ E longitude. Topographically, the upper region of the river basin is characterized by complex rugged terrain. The elevation ranges between 270 and 4000 m above the mean sea level (Figure 1). Rainfall shows both unimodal (upper and central region) and bimodal for the southern parts (Jillo et al. 2017). The annual rainfall takes a range between 400 mm in the south to 1900 mm in the high elevation areas. Rainfall in the study region is classified into three seasons, namely Kiremt (June to September), Belg (March to May) and Belg (October to February). However, the dominant rainfall season varies spatially in the Omo-Gibe river basin. Omo-Gibe basin is also categorized into three regions, namely upper region, middle region, and lower region, based on the contribution of seasonal to the total annual rainfall. The upper region is where the Kiremt rainfall contributes more than 50 % of the total annual rainfall. It represents the last third of the grid points in Figure S1. The lower region represents the lower one-third of the grid points where Kiremt season contributes only less than 30 % of total annual rainfall. For this region, the dominant rainy season is Belg (Figure S1). In between the two regions, lies the

Middle region represented by the middle one-third of the grid points in which Kiremt rainfall contributes between 30 to 50% of annual rainfall.

The mean annual temperature in the basin varies between 17 °C and 29 °C (MoWR, 1996). Highland and lowland soils prevail the basin. Highland soils in the study region are characterized by moderate natural fertility while lowland soils are generally coarse-grained with nutrient-poor soil. Humic nitisol (27.4 %) and himic alisol (18.1 %) are the dominant soils types in the basin. Cultivation in the low lands is usually constrained by moisture deficiency due to warm climate (MoWR, 1996). The total mean annual flow is estimated to be 16.6 Billion cubic meter (MoWR, 1996).

The elevation, total annual rainfall and annual mean values of the climatic elements for the grid locations considered in the current study are given in Table S1. Basin-wide, the corresponding measures of central tendencies of the climatic elements are shown in Table S2. High variations in temperatures, relative humidity, wind speed, and solar radiation reflect a wide-range of agro-ecological zones that are encompassed by the basin.

The dominant land use/land cover (Figure 1) in the basin is woodland and natural forest (both combined account for about 85 %). Cultivation land is dominant only in the highland region of the basin. Cultivation dominates in the upper region of the basin while the flatter lowlands of the northern catchments are normally used for eucalyptus tree plantations instead of cultivation. The eastern part of the basin is characterized as one of the most densely populated area in Ethiopia and, in turn, as intensively farmed areas in the basin. Both the southern part and deep gorges are less populated and, hence, are covered with natural vegetation (Woodroofe, 1996). Omo and Mago national parks as well as Tama wildlife reserve are found in the lower part of the basin (Figure S2). Three cascaded hydropower schemes, such as Gibe I (184 MW), Gibe II (240 MW) and Gibe III (1870 MW), are under operation in the study area (Figure S2). Upstream hydropower generation enables Kuraz Sugar Development (around 175,000 ha) in the lower Omo valley.

3. Data and Methodology

3.1. Data

In this study, the NCEP global weather data, i.e. CFSR (Saha et al. 2010) were used. Daily high resolution data were downloaded for the period 1979 to 2013 from https://globalweather.tamu.edu. The climatic parameters acquired were wind speed, precipitation, solar radiation, and relative humidity at 0.25 X 0.25 ° spatial resolution covering the study region. Applicability of CFSR data for hydro-climatological studies in data-scare regions like Abay river basin in Ethiopia was found very promising. Fuka et al. (2013) reported for Abay watershed that streamflow using CFSR data is equivalent to streamflow simulated using ground-observed rainfall data. Worqlul et al (2014) indicated that rainfall volume and pattern are captured better using CFSR rainfall data at Lake Tana sub-basin. Dile and Srinivasan (2014) also reported that CFSR data for hydrological modeling is a good alternative for data-scare region.

3.2. Description of the six evapotranspiration estimation methods

Based on the data required, the evapotranspiration calculation methods are categorized into temperature-based (HS, BC and TH), radiation-based (PT and MK) and combination methods (FAO-PM).

4.1.1. Blaney-Criddle method

The Blaney-Criddle method was established in the United States but has been extensively exercised in various regions (Doorenbos et al. 1977). The coefficient of the BC was adjusted by the FAO in harmony with relative humidity, sunshine hours and wind speed, and it is recommended for data-scare areas (Doorenbos et al. 1977). This method only considers temperature element at a particular region for computing reference evapotranspiration as follows:

$$ET_o = \delta(0.46T_m + 8) \qquad (1)$$

where δ is the mean daily percentage of annual day length in hours as a function of the latitude of region and T_m is the mean temperature (°C).

4.1.2. Thornthwaite Method

Thornthwaite (1948) suggested an empirical equation used to compute reference evapotranspiration through heat index and temperature. The equation relates evapotranspiration and mean air temperature. in the following fom:

$$PET = ET_{non-corrected}\left(\frac{N}{12}\right)\left(\frac{d_m}{30}\right) \qquad (2)$$

$$ET_{noncorrected} = 16\left(\frac{10T_m}{I}\right)^{\alpha} \qquad (3)$$

$$I = \sum_{i=1}^{12}\left(\frac{T_{m_i}}{5}\right)^{1.514} \qquad (4)$$

where $ET_{non\text{-}corrected}$ is the gross monthly evapotranspiration calculated over 30 days long with a theoretical 12 hours of sunshine per day; N is the maximum day length in hours expressed as a function of the month and latitude; I is the monthly heat index; d_m is the number of days per month; T_m is the mean temperature (°C); and finally

$$\alpha = 0.49239 + 1792*10^{-5}I - 771*10^{-7}I^2 + 675*10^{-9}I^3 \quad (5)$$

4.1.3. Priestley-Taylor method

To make Penman-Monteith (Monteith, 1965) equation less data demanding, Priestley and Taylor (1972) substituted the aerodynamic term by an empirical multiplier. They estimated the actual evaporation to be higher than the potential evaporation by a factor of 1.26 representing the aerodynamic term. PT requires only temperature and long-wave radiation to compute the PET by the following equation:

$$PET = 1.26 \frac{\Delta}{\Delta + \gamma} (R_n - G) \frac{1}{\lambda} \qquad (6)$$

where, Δ is the slope of vapor pressure-temperature curve (kPa °C^{-1}); γ is the psychrometric constant (kPa °C^{-1}); R_n is the net radiation of the crop surface (MJm^{-2}day^{-1}); G is the soil heat flux d (MJm^{-2}day^{-1}); λ is the latent heat of vaporization (MJ kg^{-1}). The slope of vapor pressure-temperature diagram (Δ) is estimated as:

$$\Delta = \frac{2503.058}{T_m + 273.3} \exp\left(\frac{17.27 T_m}{T_m + 237.3}\right) \qquad (7)$$

The Psychrometric constant (γ) is calculated as follows:

$$\gamma = 0.665 * 10^{-3} * P \qquad (8)$$

where P is the atmospheric pressure, which is calculated for different elevation points as:

$$P = 101.3 \left(\frac{293 - 0.0065 * Z}{293}\right)^{5.26} \qquad (9)$$

where Z is elevation of the climate station (m).

The net radiation (R_n) is given by:

$$R_n = R_{ns} - R_{nl} \qquad (10)$$

where R_{ns} and R_{nl} are the net shortwave and longwave radiations (MJ m^{-2} day^{-1}), respectively, where R_{ns} = 0.77R_s. R_{nl} can be determined based on the corrected Stefan-Boltzmann law for cloudiness and humidity as given below:

$$R_{nl}=\sigma\left[\frac{T^4{}_{max,K}+T^4{}_{min,K}}{2}\right]\left(0.34-0.14\sqrt{e_a}\right)\left(1.35\frac{\left(a_s+b_s\frac{n}{N}\right)R_a}{0.75R_a}\right)-0.35 \qquad (11)$$

where $T_{max,K}$ and $T_{min,K}$ are the maximum and minimum absolute temperatures, respectively, during a 24-hour period (K=°C + 273.16), and σ is the Stefan-Boltzmann constant (4.903*10^{-9} MJ K^{-4} m^{-2} day^{-1}).

4.1.4. Makkink Method

Makkink (1957) simplified the method for PET estimation by the use of only two parameters, namely radiation and temperature:

$$PET=0.61\frac{\Delta}{\Delta+\gamma}\frac{R_s}{\lambda}-0.12 \qquad (12)$$

where Δ is as defined before in Eq. (7); γ is as defined before in Eq. (8); a λ is the latent heat of vapor and equals 58.5 MJ kg^{-1}; and R_s is the solar radiation of the crop surface in MJm^{-2} day^{-1}.

$$PET_{Mak}=\frac{\frac{0.61*\Delta}{\Delta+\gamma}*R_s}{58.5}-0.12 \qquad (13)$$

where R_s is calculated following the procedure proposed by Allen et al. (1998) which links the surface shortwave radiation to the extraterrestrial radiation and the daily duration of sunshine as:

$$R_s=\left(a_s+b_s\times\frac{n}{N}\right)\times R_a \qquad (14)$$

where a_s and b_s are regression constants having the values 0.25 and 0.50, respectively; n is the daily hours of sunshine; and N is the day length in hours. Then, for clear-sky days (n = N), $R_{s\ clear}$ can be calculated as:

$$R_{s\,clear} = 0.75\, R_a \tag{15}$$

where R_a represents the extraterrestrial radiation (MJ m^{-2} day^{-1}) calculated according to Allen et al. (1998).

4.1.5. Hargreaves-Samani method

Depending on lysimeter data, Hargreaves and Samani (1985) recommended a method for computing the potential evapotranspiration considering minimum and maximum temperatures and extraterrestrial radiation. The HS equation is a simple method proposed as an alternative to the physically-sound but data-demanding FAO-PM (Allen et al. 1998). The equation is formulated as follows:

$$PET = 0.0023\left(T_m + 17.8\right)\left(T_{max} - T_{min}\right)^{0.5} \times R_a \tag{16}$$

where T_{max}, T_m, and T_{min} are the maximum, mean and minimum temperatures (°C), respectively, and R_a is the extraterrestrial radiation (MJ m^{-2} day^{-1}).

4.1.6. FAO Penman-Monteith equation

The FAO Penman-Monteith equation is a physically based method taking into account most relevant atmospheric processes. It can be used to develop reference potential evapotranspiration using the FAO parameterization (Allen et al. 1998). FAO-PM is a globally used standard reference evapotranspiration estimation method (Allen et al. 1998). This is a combination method of the aerodynamic and radiation terms as follows:

$$ET_o = \frac{0.408\,\Delta\left(R_n - G\right) + \gamma \dfrac{900}{T + 273} u_2 \left(e_s - e_a\right)}{\Delta + \gamma\left(1 + 0.34\, u_2\right)} \tag{17}$$

where ETo is the grass reference evapotranspiration (mm day^{-1}); R_n is the net radiation of the crop surface (MJm^{-2} day^{-1}); G and γ are as defined before in Eq. (6); T is the mean air temperature at 2 m height (°C); u_2 is the wind speed at 2 m height (m s^{-1}); e_s and e_a are the saturation and actual vapor pressures (kPa); Δ is the slope of vapor pressure-temperature curve (kPa°C^{-1}).

3.3. Comparison of PET methods using statistical metrics

To quantitatively measure the accuracy and reliability of the PET methods, seasonal and annual PET evapotranspiration estimates obtained by each method were compared with the ETo calculated using the FAO-PM. Three commonly used performance metrics were applied in this study. The Kendall correlation (Kendall, 1948) explains the correspondence between the FAO-PM ETo and the candidate PET approaches. To quantify the deviation of the PET using the candidate approaches from ETo obtained by FAO-PM, the root mean square error (RMSE) and the percentage bias error (PE) were used. The RMSE indicates how concentrated the data is around the line of best fit.

3.4. Spatio-temporal trend analysis

Trend analysis was implemented using Mann-Kendall (Mann, 1945; Kendall, 1975) test for the period 1979 to 2013 to check if the PET and ETo as well as their contributing climate variables, such as mean, minimum and maximum temperatures, rainfall, wind speed, relative humidity and radiation, have increased or decreased. The trend rates were computed for all the grid points on annual and seasonal scales.

The Mann–Kendall test (Mann, 1945; Kendall, 1975) is a non-parametric test applied to analyze the existence of a monotonic trend. The null hypothesis of the test is such that no change exists in the mean of a time series versus the alternative hypothesis of a decrease or an increase in mean of the series over time. Kendall’s statistic S is calculated as follows:

$$S=\sum_{i=1}^{n-1}\sum_{j=i-1}^{n} Sgn\left(X_j-X_i\right) \tag{18}$$

$$Sgn\left(X_j-X_i\right)=\begin{cases}+1\, if\left(X_j-X_i\right)>0\\ 0\, if\left(X_j-X_i\right)=0\\ -1\, if\left(X_j-X_i\right)<0\end{cases} \tag{19}$$

where n is the number of observations, X_j and Xi are sequential data (j > i), and Sign (X_j−X_i) is a sign function that indicates whether the difference is positive or negative. The Statistic S, which is normally distributed with zero mean and variance, is calculated as:

$$Var\left(S\right)=\frac{\left[n\left(n-1\right)\left(2n+5\right)-\sum_{i=1}^{m} t\left(t-1\right)\left(2t+5\right)\right]}{18} \tag{20}$$

where n is length of data records, t is the size of the i^{th} tie, m is the number of ties, and ∑ is the summation of all ties.

The current study used the Mann-Kendall trend test by considering the effective sample size approach and removing all autocorrelations that are significant at the 95% confidence level. The variance of the test was adjusted as suggested by Yue and Wang (2004):

$$Variance^{\text{¿}}\left(S\right)=Variance\left(S\right)\frac{m}{m^{\text{¿}}} \tag{21}$$

where Variance*(S) is the adjusted variance, Variance (S) is the variance of the Mann-Kendall statistic prior to the adjustment, m is the actual sample size of the time series under study and m* is the effective sample size, which is calculated as follows:

$$m^{\text{¿}}=\frac{n}{1+2.\sum_{k=1}^{n-1}\left(1-\frac{k}{n}\right)r_k} \tag{22}$$

where r_k is the significant lag-k serial correlation coefficient calculated following Yue and Wang (2004):

$$r_k = \frac{\frac{1}{n-k}\sum_{t=1}^{n-k}\left\{X_t - \left[\frac{1}{n}\sum_{t=1}^{n} X_t\right]\right\}\left\{X_{t+k} - \left[\frac{1}{n}\sum_{t=1}^{n} X_t\right]\right\}}{\frac{1}{n}\sum_{t=1}^{n}\left\{X_t - \left[\frac{1}{n}\sum_{t=1}^{n} X_t\right]\right\}^2} \quad (23)$$

Mann-Kendall statistic Z is estimated below:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} \; if \; S>0 \\ 0 \; if \; S=0 \\ \frac{S+1}{\sqrt{Var(S)}} \; if \; S<0 \end{cases} \quad (24)$$

where Z is the standard normal variable indicative of increasing and decreasing trends with positive and negative values, respectively.

The trend magnitude is obtained as the slope of the trends in the non-parametric Mann-Kendall test using the Theil-Sen's estimator (β) as follows:

$$\beta = Median\left[\frac{X_j - X_i}{j-i}\right] for\; all\; i<J \quad (25)$$

where X_j and X_i are sequential data (j>i). A positive β indicates an increasing trend and vice versa.

3.5. Multiple regression

To opt the attribution of the variation in PET or ETo, a multiple regression analysis was carried out on each grid point by taking into account the series of PET or ETo as a dependent variable and the four climatic variables, viz minimum and maximum temperatures, relative humidity, wind speed, and radiation, as independent variables. A standardized beta coefficient estimates how strongly each individual independent variable influences the dependent variable. The larger the absolute value of the standardized beta coefficient, the bigger the influence of the independent variable on dependent variable. Standardized beta coefficients have standard deviations as their units. It is the amount of change in the dependent variable per unit of change in the independent variable. A positive standardized beta coefficient implies that the outcome variable will increase by the beta coefficient value for every one-unit increase in the predictor, and vice-versa.

4. Results

4.1. Best performing PET approach

The performance of the PET methods were compared with the ETo calculated using the FAO-PM. The plots of the relationships between the candidate approaches and the FAO-PM method are presented in Figure S3 using daily mean values. All the relationships are non-linear with coefficient of determination (R^2) ranging from 0.34 to 0.64. The HS correlates better with FAO-PM than the other candidate approaches. Next to HS is BC, which shows R^2 of 0.63, whereas PT is the least performing approach in terms of the variations of FAO-PM estimates it explains. The HS has a least RMSE (0.8 mm/day) and lowest percentage bias error (−2.5%) for daily evapotranspiration estimations.

The best performing PET approach across the grid points is given spatially in Figures 2 and 3 on annual and seasonal scales in terms of Kendall correlation, percent bias error and RMSE. It is striking that HS performs better spatially than the remaining candidate approaches on the annual scale with reference to all the performance metrics. However, the seasonal distribution of the best performing approach varies from region to region. Below is the main description of the results with reference to each performance indicator. For details on the sub-regional results, the reader is referred to the supplementary information.

4.1.1. Kendall correlation

Table 1 indicates the number of grid points with significant and highly significant Kendall correlation between the candidate approaches and FAO-PM method in the lower, middle and upper regions of the basin on the annual and seasonal scales. HS and MK show higher correlation coefficient on the annual and seasonal scales. HS shows either better or comparable performance in terms of Kendall correlation and number of grids with significant correlation for the three regions.

4.1.2. Percentage Bias Error

Percentage bias errors of the estimates obtained using the candidate approaches in comparison to those made by FAO-PM method are indicated in Figure S4. HS shows lower percentage bias error on the annual and seasonal scales for all the three regions. It is worth mentioning that the percentage bias error varies both in magnitude and sign between the time scales and the grid locations.

4.1.3. RMSE

The RMSE for the candidate approaches in comparison to FAO-PM method are shown in Figure S5. On the annual scale, the RMSE in the lower region is smaller than in the middle and upper regions. Relatively smaller RMSE manifests in the middle region in Belg and Bega seasons. The candidate approaches on the annual and seasonal scales demonstrate consistent increase of RMSE from the lower to the higher region (Figure S5). Using PT, RMSE diminishes in Kiremt from the lower to the upper region. For almost all the grid points, the RMSEs of HS are similar on the annual and seasonal scales except for grid points located in the lower region, where the seasonal RMSE is higher than that of the annual one.

4.1.4. Number of grid points with better performance metrics

Large number of grid points show strongest Kendall correlation (54), lowest percent error (60) and lowest RMSE (57) for HS on the annual scale (Figure S6). In Kiremt season, HS outperformed in terms of percentage bias error (59 grid points), and MK in terms of RMSE (54 grid points) and Kendall correlation (50 grid points). For Belg season, HS performs the best in terms of Kendall correlation (49 grid points), RMSE (55 grid points) and percentage bias error (32 grid points). Similarly, HS surpasses considering Kendall correlation at 43 grid points, RMSE at 53 grid points and percentage bias error at 40 grid points in Bega season. As indicated in Figure S6, the performance of all the candidate approaches except HS varies depending on the time scale (annual or seasonal) under consideration and the given performance metrics.

4.1.5. Spatial distribution of PET and ETo

The spatial distribution of the annual PET estimated by the candidate approaches in comparison to the annual ETo obtained by FAO-PM is shown in Figure 4. These results indicate underestimation by TW at almost all the grid points in the middle and lower regions. BC underestimates the annual FAO-PM value mainly at the grids located in the lower region. MK underestimates FAO-PM ETo at the grids situated in the lower region but displays overestimates at the grids existing in the upper region. Estimates by both HS and MK resemble the FAO-PM values at the grids lying in the middle region. However, the grids in the upper region indicate slight overestimation by HS and MK. PT shows huge overestimation of the annual ETo at the grids found in the upper and middle regions. The grids in the upper and middle regions show annual PET by HS comparable to ETo of the FAO-PM. All the candidate approaches underestimate the FAO-PM values at the grids located in the lower region although PT is relatively comparable to FAO-PM.

4.2. Trends in candidate PET approaches

The number of grid points with significant annual and seasonal trends for various PET approaches is presented in Table 3. The results depict that number of grid points with significant trend and its magnitude vary among the candidate approaches and seasons. Temperature-based approaches indicate higher number of grids with significant trends (BC followed by TW and HS) compared to the other approaches.

Figures 5 and S7 to S9 give the spatial distribution of the trend magnitude of PET on annual and seasonal scales using Sen's slope estimator for the candidate approaches. Using both BC and TW, PET shows statistically significant trend for all grid points on the annual and Bega seasonal scales. For BC, PET shows similar pattern of trend as that of the maximum temperature. On the annual scale, the multiple regression analysis also shows that maximum temperature is the most influential parameter with standardized beta coefficient of 0.88. The mean annual standardized beta coefficients under BC are the lowest in comparison with the other candidate approaches for radiation (−0.16), minimum temperature (0.14), wind speed (0.07) and relative humidity (0.07), respectively.

TW is dominated with both minimum and maximum temperatures (Figures 5 and S7 to S9). The lower region is influenced by minimum temperatures and manifested very high trend magnitude. In the middle region, where the trend magnitude for maximum and minimum temperate were mild, PET trend magnitude is the lowest among the PET trends for the three sub-regions. The mean annual standardized beta coefficients were highest for minimum temperature (0.44) followed by maximum temperature (0.43), and smallest for wind speed (0.12) and relative humidity (0.10). PET is not sensitive to radiation.

Using HS, the PET trend magnitude is decreasing. Multiple regression analysis showed that HS is mainly influenced by maximum temperature but offset by minimum temperature. As a result, downstream region with lower trend magnitude in maximum temperature and higher trend magnitude in minimum temperature showed non-significant or significant decreasing trend. The mean annual standardized beta coefficients for the basin were highest for maximum and minimum temperatures (1.79 and −1.02), and lowest for radiation (−0.07), wind speed (0.03) and relative humidity (−0.03). These results indicated that 10% increase in either maximum temperature or wind speed results in 17.9% or 0.3% increase in PET, respectively. But 10% decrease in minimum temperature, radiation and relative humidity would result in 10.2%, 0.7% and 0.3% increase in PET respectively.

PT and MK on annual scale portrayed increasing trends in PET in the upper region of the study area, which has shown significant increasing trend in radiation and decreasing trends in relative humidity. Multiple regression analysis also indicated that radiation is the dominant variable influencing PET in both PT and MK. The mean annual standardized beta coefficients under PT were highest for radiation (1.04) and relative humidity (0.49), intermediate for maximum temperature (0.33), and smallest for minimum temperature and wind speed (0.04 and 0.02, respectively). The mean annual standardized beta coefficients for the study basin under MK were highest for radiation (0.91) and lowest for minimum temperature (−0.17), relative humidity (−0.09), maximum temperature (0.08), and wind speed (0.01).

Trend magnitude for annual PET using FAO-PM is highest for the basin manifested with higher warming rate of daytime temperature, significant increasing trend in radiation and significant decreasing rate in relative humidity (Figures 5 and 6). The mean annual standardized beta coefficients for the study basin under FAO-PM were the highest for wind speed (0.43), intermediate for maximum temperature (0.32) and radiation (0.28), and smallest for minimum temperature (0.13) and relative humidity (−0.10). These results imply that a 10% increase in maximum and minimum temperatures, wind speed, radiation would result in a 3.2%, 1.3%, 4.3% and 2.8 % increase in PET, respectively whereas a 10% decrease in relative humidity would result in a 1% increase in PET. Grids points with significant decreasing trends in wind speed manifested non-significant trend magnitude for FAO-PM. Number of grid points with significant trend using FAO-PM are far less in Belg and Bega seasons than that for annual and Kiremt seasons. Except BC and TW, all the approaches portrayed significant decreasing trends in Belg season for grids in the lower region. Kiremt season portrayed significant increasing trends for grids in the lower region for the majority of the PET approaches. The annual trend magnitude is highest compared to the seasonal trend magnitudes for almost all grid points and candidate approaches. It is worth mentioning that the number of grid points with significant trends and trend magnitude vary from region to region and among seasons (Figures 5 and S7 to S9).

Annual and Kiremt season rainfall show significant decreasing trends for the upper most region (Figure S10). This region also showed highest warming rate during the daytime, higher radiation rate, and declined relative humidity.

4.3. Trends in input climatic parameters for PET

Trend magnitude using Sen's slope estimator for input climatic variables are indicated in Figure 6. For radiation, 24 grid points show statistically significant increasing trend whereas one grid point only shows decreasing trend. The significant trends in radiation are concentrated in the upper region of the study catchment, which is characterized by relatively higher humidity and lower temperature. Similar to radiation, significant trends in relative humidity exhibits in the upper region. Out of 26 grid points showing significant trends, only 2 grid points indicate increasing trends while the remaining ones show decreasing trends). Not only few grid points (10 grid points) show significant decreasing trends in wind speed, but they also manifest weak trend magnitudes. Those grid points with significant decreasing trend are found in the western part of the middle region, which is characterized by mean temperature of 20.4 °C (less than basin average) and relative humidity of 65.8 % (slightly higher than basin average).

The maximum, minimum and mean temperatures show highly significant trends for all grid points on the annual scale (Figure 6). The trend magnitude for the maximum temperature ranges from 0.2 to 0.9 °C/decade. It decreases while moving from the upper region to the lower region. The warming rate during daytime in the sub-humid (upper) region of the catchment is higher than that in the dry arid (lower) region. The minimum temperature manifests opposite patterns on the trend magnitude (Figure 6), i.e the trend magnitude during night is decreasing in the direction from the upper region to the lower region and ranges from 0.3 to 0.5 °C/decade. Lastly, the mean temperature also shows similar patterns in trend magnitude as that of the maximum temperature, i.e. increasing from the lower region to the upper region, but at rates ranging from 0.3 to 0.6 °C/decade.

5. Discussion

5.1 Performance of PET approaches in the context of literature

This study has shown that the radiation-based approaches are outperformed by temperature-based approaches. Among the latter set of approaches, HS is the best in light of bias error, Kendall correlation and RMSE. It followed the same spatial trend as that of FAO-PM across the study region. The method finds several advocates in literature. Tabari (2010) reported that the HS equation was most accurate under the humid condition in Iran. Li et al. (2018) recommended HS in opposition to TW for PET estimation. Rahimikhoob et al. (2012) reported that HS compared very well with FAO-PM values in northern Iran. Both our results and these studies contest the argument that favors the radiation-based methods over their peers, which are temperature in the evaluation of PET in eastern Asia (Xu and Chen, 2005; Tukimat et al. 2012; Jadhav et al. 2015). The result of our study is also in disagreement with that conducted by Trajkovic and Kolakovic, (2009), who discerned relatively higher error with HS compared to TW and PT for humid locations in Western Balkans.

Among the radiation-based methods, MK exhibits better performance than PT, especially in the upper and middle regions of the Omo-Gibe river basin which is characterized by relatively high humidity, less temperature and less evapotranspiration. Compared to the other approaches under consideration in the present study, it is established that TW performs poorly under the humid climate in southwestern China (Lang et al. 2017). This result is in accord with results obtained by Chen et al. (2005) and Lu et al. (2005) that TW performed worse in China and Southeastern United States.

5.2 Attributing trends of PET in the context of literature

In the current study, PET has shown highest increasing rate in regions where temperature is increasing with higher rates. The result of significant increasing trends in temperatures is in agreement with results obtained by Gebrechorkos et al. (2019), who indicated significant increasing trends in maximum and minimum temperatures in Ethiopia. Warming climate does not always increase the PET, but literature reports both increasing and decreasing trends in PET. Increasing trends in PET, for instance, were indicated by Espadafor et al. (2011) for southern Spain and by Kousari and Ahani (2012) for Iran. Conversely, Jhajharia et al. (2012), Irmak et al. (2012) and Shan et al. (2016) found decreasing PET trends for India, the United States and northwestern China, respectively. Inverse relationship has been exhibited in the present study area between the PET – using both HS and MK – and minimum temperature likewise in different parts of the world (Roderick et al. 2007; Jung et al. 2010; Hans et al. 2012; Brutsaert, 2013; Padmakumari et al. 2013; Bian et al. 2020).

Different trend magnitudes of rainfall and input climatic parameters for PET/ETo are manifested in the lower, middle and upper regions of the Omo-Gibe basin. Spatially heterogeneous changes of temperatures, wind speed, relative humidity, and solar radiation have been observed in different parts of the world which resulted in varying PET (Sherwood et al. 2010; Celik and Cengiz, 2014; Shan et al. 2016; Liu et al. 2017). Wind speed in Africa is generally decreasing (Wu et al. 2018). This increase could be one of the key factors reducing the atmospheric water demand (Song et al. 2010). The dominant climate variables playing the role in changing PET varies with location and climate. For instance, Xu et al. (2006) noted that decreasing trends in the wind speed and net total radiation are main causes of the declining PET in the Changjiang catchment, China. Liu et al. (2010) attributed the increasing PET to a rise in temperature and declining wind speed in the Yellow River Basin, China. Huo et al. (2013) indicated that wind speed is predominantly changing PET in the arid northwestern regions of China. In the Loess Plateau of China, declines in both solar radiation and wind speed and an increase in actual vapor pressure were found responsible for the decrease in PET (Ning et al. 2018). Similarly, results for Iran demonstrate varying conclusions. Although Mosaedi et al. (2016) reported the changes in maximum temperature and relative humidity as attributes for changes in PET in Iran, others found that actual vapor pressure and temperature to be the main and the least influential variables, respectively, in the changes in PET noted for Iran (Sharifi and Dinpashoh 2014). In some arid environments, Nouri et al. (2017) showed that the change of wind speed is an example of underlying cause of the trend in annual PET.

5.3 Influence of elevation and rainfall on ETo (FAO-PM)

Elevation strongly impacts climatic parameters thereby affecting PET. The relationship between annual PET using FAO-PM and elevation as well PET with rainfall distribution is shown in Figure 7. Results indicated that annual PET using FAO-PM significantly correlated with both elevation of the grid points and annual rainfall amount. Yang et al. (2019) revealed that ETo using FAO-PM decreased as the elevation increased in northwest China. Thomas, (2000) reported a positive relation between evapotranspiration change and station elevation in southwest China. The correlation of PET with annual rainfall amount is stronger than that of altitude.

6. Conclusions

Aiming at selecting appropriate methods for estimating evapotranspiration in Omo-Gibe River Basin in Ethiopia, the performance of five simple evapotranspiration methods has been examined in this study using the CFSR climatic data. To extensively explore the changing behavior of PET in the basin, the trends in annual potential evapotranspiration PET, maximum and minimum temperatures, wind speed, relative humidity, solar radiation and rainfall have also been quantitatively studied for the period 1979−2013. Spatio-temporal analysis was carried out for various PET approaches on a seasonal basis. The relative contribution of various climatic variables to PET trend has been examined. Besides, the spatial distributions and trends of the climatic variables were investigated to further explain the most influential climatic parameter for various PET approaches.

The magnitude of statistical performance metrics used varies in space and from season to season for the candidate approaches. Among the five evapotranspiration methods, the temperature-based HS portrayed similar magnitude of PET as that exhibited by the FAO-PM method at annual scale. HS outperforms in the upper and middle regions of the Omo-Gibe River Basin which are characterized by relatively high humidity, less temperature and less evapotranspiration. MK is comparable with FAO-PM in the middle region of the river basin. For the lower region, HS and MK perform better in terms of RMSE and number of grids with significant Kendall correlations. PT is the best alternative to FAO-PM in terms of percentage error in the lower region. All the candidate approaches underestimated FAO-PM estimates of evapotranspiration in the lower edge of the river basin, which is a region characterized by very hot, less humid and high evapotranspiration climate conditions. However, PT portrays FAO-PM in terms of PET magnitude in the lower edge of the study area. In view of the limitations in the availability and reliability of the climate data in the study region, the adequate performance of HS must be highlighted since it only requires measuring air temperatures.

The trend magnitude and direction of the climatic input parameters for PET/ETo estimates varied spatially, but none of the changes in PET or ETo could be attributed to the changes in a single climatic variable. Depending on the candidate approach and time-scale of analysis (seasonal or annual) under consideration, the results indicated that the number of grid points with significant trend and magnitude varied between the different regions across the basin. Over the period 1979−2013, the annual FAO-PM PET increased with higher rate while the annual and Kiremt season rainfall declined in the upper region of the study river basin. Given the dominant rain-fed agricultural activities, the ramifications of a continuation of this trend might manifest in food production/security due to reducing soil moisture availability. Therefore, soil moisture conservation during the rainy season might support proper water management in upper region of the Omo-Gibe river basin. In contrary, the decline in PET for the main rainy season coupled with higher rate of increase in rainfall in the lower region might amplify water availability thereon through reduced irrigation demand for sugarcane plantation, less reservoir water evaporation and increased water gain through rainfall on the reservoirs. The increasing PET, however, noted during seasons with less rainfall might further reduce soil moisture availability and increase evaporation from reservoirs, thus might increase irrigation water demand in the lower region. Therefore, water management programs in the study river basin should consider these negative and positive implications.

Acknowledgements

The National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) products used in this study were obtained from the Global Weather Data for Soil and Water Assessment Tool (SWAT) (https://globalweather.tamu.edu).

CRediT authorship contribution statement

Tekalegn Ayele Woldesenbet: Conceptualized the study, contributed to the design of the methodology, performed the formal analysis and wrote up the original draft. **Nadir Ahmed Elagib** contributed to the design of the methodology and writing of the manuscript and critically reviewed and edited the final manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

References

Allen RG, Clemmens AJ, Burt CM, Solomon K, O'Halloran T (2005) Prediction accuracy for project-wide evapotranspiration using crop coefficients and reference evapotranspiration. J Irrig Drain Eng 131: 24–36.

Allen RG, Pereira LS, Raes D, Smith M (1998) Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements. FAO Irrigation and Drainage Paper 56; FAO-Food and Agriculture Organization of the United Nations Rome: Rome, Italy.

Bian Y, Dai H, Zhang Q, Yang L, Du W (2020) Spatial distribution of potential evapotranspiration trends in the inner Mongola Autonomous Region (1971−2016). Theor Appl Climatol. DOI: 10.1007/s00704-020-03154-y.

Bogawski P, Bednorz E (2014) Comparison and validation of selected evapotranspiration models for conditions in Poland (Central Europe). Water Resour Manage 28: 5021–5038. DOI: 10.1007/s11269-014-0787-8.

Brutsaert W. (2013) Use of pan evaporation to estimate terrestrial evaporation trends: the case of the Tibetan Plateau. Water Resour Res 49:3054–3058.

Celik FD, Cengiz E (2014) Wind speed trends over Turkey from 1975 to 2006. Int J Climatol 34(6): 1913–1927. DOI: 10.1002/joc.3810.

Chen D, Gao G, Xu C, Guo J, Ren G (2005) Comparison of the Thornthwaite method and pan data with the standard Penman–Monteith estimates of reference evapotranspiration in China. Clim Res 28: 123–132.

Dile YT, Srinivasan R (2014) Evaluation of CFSR climate data for the hydrologic prediction in data-scares watersheds: An application in the Blue Nile River Basin. J Am Water Resour Assoc 50: 1226−1241.

Ding R, Kang S, Li F, Zhang Y, Tong L (2013). Evapotranspiration measurement and estimation using modified Priestley-Taylor model in an irrigated maize field with mulching. Agr Forest Meteorol 168: 140-148. DOI: 10:1016/j.agrformet.2012.08.003.

Dinku T, Block P, Sharoff J, Hailemariam K, Osgood D, del Corral J, Cousin R, Thomson MC (2014). Bridging critical gaps in climate services and applications in Africa. Earth Perspectives 1(1): 15.

Dinku T, Thomson MC, Cousin R, del Corral J, Ceccato P, Hansen J, Connor S.J (2018). Enhancing national climate services (ENACTS) for development in Africa. Clim Dev 10(7): 664-672.

Djaman K, Balde AB, Sow A, Muller B, Irmak S, NDiaye MK, Manneh B, Moukoumbi YD, Futakuchi K, Saito K (2015) Evaluation of sixteen reference evapotranspiration methods under sahelian conditions in the Senegal River Valley. Journal of Hydrology: Regional Studies, 3, 139–159. DOI: 10.1016/j.ejrh.2015.02.002.

Doorenbos J, Pruitt WO, Aboukhales A, Damagnez J, Dastane NG, Van Den Berg C, Rijtema PE, Ashford OM, Frere M (1977) Crop water requirements. FAO Irrigation and Drainage. Rome: FAO. Paper no. 24: 109–110.

Espadafor M, Lorite IJ, Gavilán P, Berengeana J (2011) An analysis of the tendency of reference evapotranspiration estimates and other climate variables during the last 45 years in Southern Spain. Agric Water Manage 98(6): 1045–1061.

Fisher JB, Melton F, Middleton E, Hain C, Anderson M, Allen R, McCabe MF, Hook S, Baldocchi D, Townsend PA, Kilic A, Tu K, Miralles DD, Perret J, Lagouarde J-P, Waliser D, Purdy AJ, French A, Schimel D, Famiglietti JS, Stephens G, Wood EF (2017) The future of evapotranspiration: Global requirements for ecosystem functioning, carbon and climate feedbacks, agricultural management, and water resources. Water Resour Res 53: 2618–2626. DOI:10.1002/2016WR020175.

Fuka DR, Walter MT, MacAlister C, Degatetono AT, Steenhuise TS, Easton ZM (2013) Using the Climate Forecast System Reanalysis as weather input data for watershed models. Hydrol Process 28(22). Doi:10.1002/hyp.10073.

Gebrechorkos SH, Hülsmann S, Bernhofer C (2019) Long-term trends in rainfall and temperature using high-resolution climate datasets in East Africa. Sci Rep 9:11376. DOI: 10.1038/s41598-019-47933-8.

Han S, Xu D, Wang S (2012) Decreasing potential evaporation trends in China from 1956 to 2005: accelerated in regions with significant agricultural influence? Agric For Meteorol 154: 44–56.

Hargreaves GH, Samani ZA (1985) Reference crop evapotranspiration from temperature. Appl Eng Agric 1: 96–99.

Huo Z, Dai X, Feng S, Kang S, Huang G (2013) Effect of climate change on reference evapotranspiration and aridity index in arid region of China. J Hydrol 492: 24–34. DOI: 10.1016/j.jhydrol.2013.04.011.

Irmak S, Kabenge I, Skaggs KE, Mutiibwa D (2012) Trend and magnitude of changes in climate variables and reference evapotranspiration over 116-yr period in the Platte River Basin, central Nebraska, USA. J Hydrol 420–421(4): 228–244.

Jadhav PB, Kadam SA, Gorantiwar SD (2015) Comparison of methods for estimating reference evapotranspiration (ETo) for Rahuri region. J Agrometeorol 17: 204–207.

Jhajharia D, Dinpashoh Y, Kahya E, Singh VP, Fard AF (2012) Trends in reference evapotranspiration in the humid region of northeast India. Hydrol Processes 26(3): 421–435. DOI: 10.1002/HYP.8140.

Jillo AY, Demissie SS, Viglione A, Asfaw DH, Sivapalan M (2017). Characterization of regional variability of seasonal water balance within Omo-Ghibe River basin, Ethiopia. Hydrolog Sci J 62(8): 1200-1215. DOI: 10.1080/02626667.2017.1313419.

Jung CG, Lee DR, Moon JW (2016) Comparison of the Penman-Monteith method and regional calibration of the Hargreaves equation for actual evapotranspiration using SWAT-simulated results in the Seolma-cheon basin, South Korea. Hydrolog Sci J 61(4): 793-800. DOI: 10.1080/02626667.2014.943231.

Jung M, Reichstein M, Ciais P, Seneviratne SI, Sheffield J, Goulden ML, Bonan G, Cescatti A, Chen J, De Jeu R (2010) Recent decline in the global land evapotranspiration trend due to limited moisture supply. Nature 467: 951–954.

Kendall MG (1948). Rank Correlation Methods. Griffin, London.

Kendall MG (1975) Rank Correlation Methods. Griffin Press: London.

Khoob AR (2008) Comparative study of Hargreaves's and artificial neural network's methodologies in estimating reference evapotranspiration in a semiarid environment. Irrig Sci 26: 253–259.

Kousari MR, Ahani H (2012) An investigation on reference crop evapotranspiration trend from 1975 to 2005 in Iran. Int J Climatol 32(15): 2387–2402. DOI: 10.1002/JOC.3404.

Lang D, Zheng J, Shi J, Liao F, Ma X, Wang W, Chen X, Zhang M (2017) A comparative study of potential evapotranspiration estimation by eight methods with FAO Penman–Monteith method in Southwestern China. Water 9: 734.

Li Z, Yang Y, Kan G, Hong Y (2018) Study on the applicability of the Hargreaves potential evapotranspiration estimation method in CREST distributed hydrological model (Version 3.0) applications. Water 10: 1882. DOI: 10.3390/w10121882.

Liu B, Chen X, Li Y, Chen X (2017) Long-term change of potential evapotranspiration over southwest China and teleconnections with large-scale climate anomalies. Int J Climatol 38(4): 1964−1975. DOI: 10.1002/joc.5309

Liu Q, Yang Z, Cui B, Sun T (2010) The temporal trends of reference evapotranspiration and its sensitivity to key meteorological variables in the Yellow River basin, China. Hydrol Process 24: 2171–2181.

Lu J, Sun G, Mcnulty SG, Amatya DM (2005) A comparison of six potential evapotranspiration methods for regional use in the Southeastern United States. J Am Water Resour Assoc 41: 621–633.

Maeda EE, Wiberg DA, Pellikka PKE (2011) Estimating reference evapotranspiration using remote sensing and empirical models in a region with limited ground data availability in Kenya. Appl Geogr 31: 251−258.

Makkink GF (1957) Testing the Penman formula by means of lysimeters. Journal of Institute of Water Engineering 11: 277–288.

Mann HB (1945) Nonparametric tests against trend. Econometrica 13: 245–259.

Monteith JL (1965) Evaporation and environment. The State and Movement of Water in Living Organism. Society for Experimental Biology 19: 205–234.

Mosaedi A, Sough MG, Sadeghi S-H, Mooshakhian Y, Bannayan M (2016) Sensitivity analysis of monthly reference crop evapotranspiration trends in Iran: a qualitative approach. Theor Appl Climatol 128: 857−873. DOI: 10.1007/s00704-016-1740-y.

MoWR (Ministry of Water Resources) (1996) Omo-Gibe River Basin integrated development master plan study: Final report; Volume I executive summary; MoWR: Addis Ababa, Ethiopia

Ning T, Liu W, Shen H, Li Z (2018) Attribution analysis of the spatial variations in potential evapotranspiration on the Loess Plateau of China by a total differential equation. Hydrology Research 49(6): 1902−1914.

Nordling L (2019). Scientists struggle to access Africa's historical climate data. Nature 574: 605-606. DOI: 10.1038/d41586-019-03202-2.

Nouri M, Homaee M, Bannayan M (2017) Quantitative trend, sensitivity and contribution analyses of reference evapotranspiration in some arid environments under climate change. Water Resour Manage 31(7): 2207−2224. DOI: 10.1007/s11269-017-1638-1

Padmakumari B, Jaswal AK, Goswami BN (2013) Decrease in evaporation over the Indian monsoon region: implication on regional hydrologic cycle. Clim Change 121: 787−799. DOI: 10.1007/s10584-013-0957-3.

Priestley CHB, Taylor RJ (1972) On the assessment of the surfaces heat and evapotranspiration using large-scale parameters. Monthly Water Review 100(2): 81−92.

Rahimikhoob A, Behbahani MR, Fakheri J (2012) An evaluation of four reference evapotranspiration models in a subtropical climate. Water Resour Manage 26: 2867–2881. DOI 10.1007/s11269-012-0054-9.

Raziei T, Pereira LS (2013) Estimation of ETo with Hargreaves–Samani and FAO-PM temperature methods for a wide range of climates in Iran. Agric Water Manag 121: 1–18.

Roderick ML, Rotstayn LD, Farquhar GD, Hobbins MT (2007) On the attribution of changing pan evaporation. Geophys Res Lett 34. DOI: 10.1029/2007GL031166.

Saha S, Moorthi S, Pan H-L, Wu X, Wang J, Nadiga S, Tripp P, Kistler R, Woolen J, Behringer D (2010) The NCEP Climate Forecast System Reanalysis. Bull Am Meteorol Soc 9(1): 1015−1058.

Senay GB, Budde M, Verdin JP, Melesse AM (2007) A coupled remote sensing and simplified surface energy balance approach to estimate actual evapotranspiration from irrigated fields. Sensors 7: 979–1000.

Shan N, Shi Z, Yang X, Zhang X, Guo H, Zhang B, Zhang Z (2016) Trends in potential evapotranspiration from 1960 to 2013 for a desertification-prone region of China. Int J Climatol 36: 3434–3445. DOI: 10.1002/joc.4566

Sharifi A, Dinpashoh Y (2014) Sensitivity analysis of the Penman-Monteith reference crop evapotranspiration to climatic variables in Iran. Water Resour Manag 28: 5465–5476. DOI: 10.1007/s11269-014-0813-x.

Sherwood SC, Ingram W, Tsushima Y, Satoh M, Roberts M, Vidale PL, Gorman PA (2010) Relative humidity changes in a warmer climate. J Geophys Res 115: D09104. DOI: 10.1029/2009JD012585

Song X, Lu F, Xiao W, Zhu K, Zhou Y, Xie Z (2019) Performance of 12 reference evapotranspiration estimation methods compared with the Penman–Monteith method and the potential influences in northeast China. Meteorol Appl 26: 83–96.

Song ZW, Zhang HL, Snyder RL, Anderson FE, Chen F (2010) Distribution and trends in reference evapotranspiration in the North China Plain. J Irrig Drain Eng 136(4): 240–247.

Tabari H (2010) Evaluation of reference crop evapotranspiration equations in various climates. Water Resour Manage 24: 2311–2337. DOI 10.1007/s11269-009-9553-8

Thomas A (2000) Spatial and temporal characteristics of potential ET trends over China. Int J Climatol 20(4): 381–396. DOI: 10.1002/(SICI)1097-0088(20000330)20:4<381::AID-JOC477>3.0.CO;2-K

Thornthwaite CW (1948) An approach toward a rational classification of climate. Geographical Revue 38: 55−94.

Trajkovic S, Kolakovic S (2009) Evaluation of reference evapotranspiration equations under humid conditions. Water Resour Manage 23: 3057–3067. DOI 10.1007/s11269-009-9423-4.

Tukimat NNA, Harun S, Shahid S (2012) Comparison of different methods in estimating potential evapotranspiration at Muda irrigation scheme of Malaysia. J Agric Rural Dev Trop Subtrop 113: 77–85.

Wagle P, Bhattarai N, Gowda PH, Kakani VG (2017) Performance of five surface energy balance models for estimating daily evapotranspiration in high biomass sorghum. ISPRS J Photogramm Remote Sens 128: 192–203.

Washington R, Harrison M, Conway D, Black E, Challinor A, Grimes D, Jones R, Morse A, Kay G, Todd M (2006). African climate change: taking the shorter route. Bull Am Meteorol Soc 87(10): 1355-1366.

Weiß M, Menzel L (2008) A global comparison of four potential evapotranspiration equations and their relevance to stream flow modelling in semi-arid environments. Adv Geosci 18: 15–23.

Woldesenbet TA, Elagib NA, Ribbe L, Heinrich J (2017). Gap filling and homogenization of climatological datasets in the headwater region of the Upper Blue Nile Basin, Ethiopia. Int J Climatol 37(4):.2122-2140.

Woodroofe R, Mascott Associates Ltd. (1996) Omo-Gibe River Basin integrated development master plan study. Final Report. Ministry of Water Resources of the Federal Democratic Republic of Ethiopia.

Worqlul AW, Maathuis B, Adem AA, Demissie SS, Langan S, Steenhuise TS (2014) Comparison of rainfall estimations by TRMM 3B42, MPEG and CFSR with ground-observed data for the Lake Tana basin in Ethiopia. Hydrol Earth Syst Sci 18: 4871−4881.

Wu J, Zha J, Zhao D, Yang Q (2018) Changes in terrestrial near-surface wind speed and their possible causes: an overview. Clim Dyn 51: 2039–2078. DOI: 10.1007/s00382-017-3997-y.

Xu C, Chen D (2005) Comparison of seven models for estimation of evapotranspiration and groundwater recharge using lysimeter measurement data in Germany. Hydrol Process 19: 3717–3734.

Xu CY, Gong L, Jiang T, Chen D, Singh VP (2006) Analysis of spatial distribution and temporal trend of reference evapotranspiration and pan evaporation in Changjiang (Yangtze River) catchment. J Hydrol 327: 81–93. DOI: 10.1016/j.jhydrol.2005.11.029

Yang Y, Chen R, Song Y, Han C, Liu J, Liu Z (2019) Sensitivity of potential evapotranspiration to meteorological factors and their elevational gradients in the Qilian Mountains, northwestern China. J Hydrol 568: 147–159. https://doi.org/10.1016/j.jhydrol.2018.10.069

Yue S, Wang CY (2004) The Mann-Kendall test modified by effective sample size to detect trend in serially correlated hydrological series. Water Resour Manag 18(3): 201−218.