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Extra Dimensions to the Calibration of Hargreaves-Samani Equation Under Data-Scarce Environment

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Abstract

Evapotranspiration estimates are paramount for understanding climatology and better water management, especially in regions notorious for recurrent droughts, high evapotranspiration losses and basins with overspilling. This study adds new dimensions to the adjustment of the Hargreaves-Samani model (HS) against the standard FAO Penman-Monteith method for estimating reference evapotranspiration. The original coefficient (C = 0.0023) and the overall exponent (E = 1.0) in HS are calibrated and validated while splitting and exchanging of odd and even years' datasets. Sudan and South Sudan are selected as a case of least studied and data-scarce countries though encompassing the largest part of the Nile basin with diverse hydroclimate zones. Implications of the proposed dimensions for the results and their usage in water management are discussed. Data splitting in the present manner reveals variation in the results between the different datasets, depending on the geographical location and the associated climate as well as the season. Thus, data splitting avoids bias towards certain mode of climate in a changing world and subsequent misinterpretation. Both C and E increase linearly with latitude from the dry sub-humid to the hyper-arid zone. The resulting latitude dependence offers interpolation and extrapolation of the constants across this large yet understudied region. Least calibration characterized the wettest months whereas largest calibration distinguished the transitional months towards the dry/cool season. Adjusting C is more suitable for the hyper-arid and semi-arid zones as well as for the hot and wet seasons. Calibrating E suits better the arid and dry sub-humid zones in addition to the dry/cool season. The present results (mis) match results reported in the literature for similar climate zones, thus opening venues for further studies elsewhere.

Research highlights

- Calibration of the coefficient and overall exponent in the Hargreaves-Samani model
- Splitting and exchange approach of odd and even years' data in the calibration and validation processes
- Considering four hydroclimate zones within two Nile countries, Sudan and South Sudan
- Station-specific and study area-wide (month-specific) adjustments are carried out
- Results vary with data splitting, latitude, season of the year and/or climate zone and have important implications for science and application

Extended author information available on the last page of the article

Keywords Evapotranspiration · Hargreaves Formula · FAO Penman-Monteith Method · Calibration · Validation · Nile · Sudan

1 Introduction

Accurate estimation of evapotranspiration plays an essential role in managing water resources as, for example, in determining the crop water requirement, irrigation scheduling and water budgets particularly in drought-prone environments. To this end, crop evapotranspiration is usually estimated by multiplying the grass reference evapotranspiration (ETo) by a suitable crop coefficient (Allen et al. 1998). The Food and Agriculture Organization version of Penman-Monteith equation (FAO-PM) has been recommended as the globally standard model for estimating ETo in all climates and for validating other models (Allen et al. 1998; Landeras et al. 2008). However, the main drawback associated with FAO-PM is the requirement for numerous meteorological data (e.g., temperature, wind speed, solar radiation and relative humidity), which are often unreliably measured or unavailable at most of the stations worldwide (Niranjan and Nandagiri 2021). To tackle this problem, considerable attention has been devoted to proposing alternative empirical methods to provide reliable estimates of ETo using fewer and readily accessible data (Raziei and Pereira 2013).

Air temperature is a key climate input in ETo formulae, and its variation is most likely the source of ETo variability (Samani 2000). Much focus has been given to developing ETo equations employing only air temperature as it is regularly recorded at most meteorological stations (Awal et al. 2020). Among these equations, the Hargreaves–Samani model (Hargreaves and Samani 1985) - hereinafter HS - has been recommended by Allen et al. (1998) as an alternative to FAO-PM. Some studies concluded the reliability of HS for estimating ETo (Hargreaves and Allen 2003; Shiri et al. 2015; Landeras et al. 2008). Others noted however the tendency of this equation to overestimate ETo in humid regions (Trajkovic 2005) and underestimate it in arid regions (Azhar and Perera 2011). Errors emerging from HS in climates with high humidity or wind speed are attributable to the exclusion of relevant inputs in the model (Quej et al. 2019). To improve the performance of HS, it is fundamental to calibrate it prior to application (Allen et al. 1998; Hadria et al. 2021).

Previous studies attempted to calibrate HS using different approaches. For example, Sentelhas et al. (2010) used data from 12 locations in Southern Ontario, Canada, for the calibration of HS coefficient 0.0023 to reduce the overestimation against FAO-PM. The adjusted version, nevertheless, was ranked in the 6th place. Aguilar and Polo (2011) calibrated the coefficient 0.0023 using climatic data from seven weather stations with varying altitudes in the Guadalfeo river watershed, Southern Spain. They showed spatio-temporal variations in the adjusted coefficient at a watershed scale. Using long-term monthly means data across different Köppen climate classes, Almorox and Grieser (2016) recommended the use of a modified HS against FAO-PM by calibrating the coefficient 0.0023 and the exponent 0.5 as well as adding another constant term. Morales-Salinas et al. (2017) undertook monthly spatial calibration for the 0.0023 based on the variability of temperatures in Maule region, central-southern Chile. The calibrated model resulted in improved estimates following validation using daily data for all the months. Xia et al. (2020) showed that the HS coefficient

0.0023 and exponent 0.5 were more suitable for semi-arid and most of arid regions than for the other climatic regions in China where calibration was needed. A regional evaluation, calibration and validation of HS performed by Awal et al. (2020) in West Texas showed underestimation of daily ETo and an improved performance through adjusting the HS coefficient. In the quest for a better performance of HS for the Omo-Gibe river basin in Ethiopia, Woldesenbet and Elagib (2021) proposed higher or lower values instead of the original constant 17.8, but extremely lower values to replace the coefficient 0.0023. Calibration of the values 0.0023 and 0.5 improved the model performance across the Northern Region of Nigeria (Ogunrinde et al. 2022).

The above literature review highlights the necessity for deeper investigation of HS before its application. It is evident that calibration of this equation yields different results even in similar climates. In data-scare regions, a way to estimate a calibrated constant of the HS is needed. There is also an exceptional gap in relevant research for a wide domain of the African climates. In this regard, a least studied and data-scarce area is Sudan and South Sudan. Based on the above background, the following research questions emerge in relation to the adjustment of HS:

(i) Does data splitting technique result in different calibrated HS constants between these data subsets?
(ii) Do the HS constants vary across diverse hydroclimates and/or over the seasons?
(iii) Can the calibrated constants be interpolated and extrapolated over a large area, especially that characterized by data scarcity?
(iv) Can any preference be given to calibrating an HS constant over others in terms of climate zone or season of the year?

Therefore, this study makes a meaningful effort to suggest new conceptual dimensions for evaluating HS against the benchmark FAO-PM to improve the potential evapotranspiration estimates across the two countries. In doing so, this study:

a) calibrates the HS coefficient and overall exponent and validates the calibrated constants across diverse hydroclimates and seasons.
b) carries out the calibration and validation processes using a data splitting and exchange approach to explore possible time dependence of and influence of climate variability on the results of each process. Instead of the traditional successive period-blocks of datasets, here we ensure involving the full climate variability in each process by exchanging independent odd and even years' datasets between the two processes.
c) explores a way to interpolating and extrapolating the adjusted constants across this large data-scarce study area.

2 Materials and Methods

Figure 1 shows the flowchart of the materials and methods used in this study. The study area is described in the Supplementary Materials.

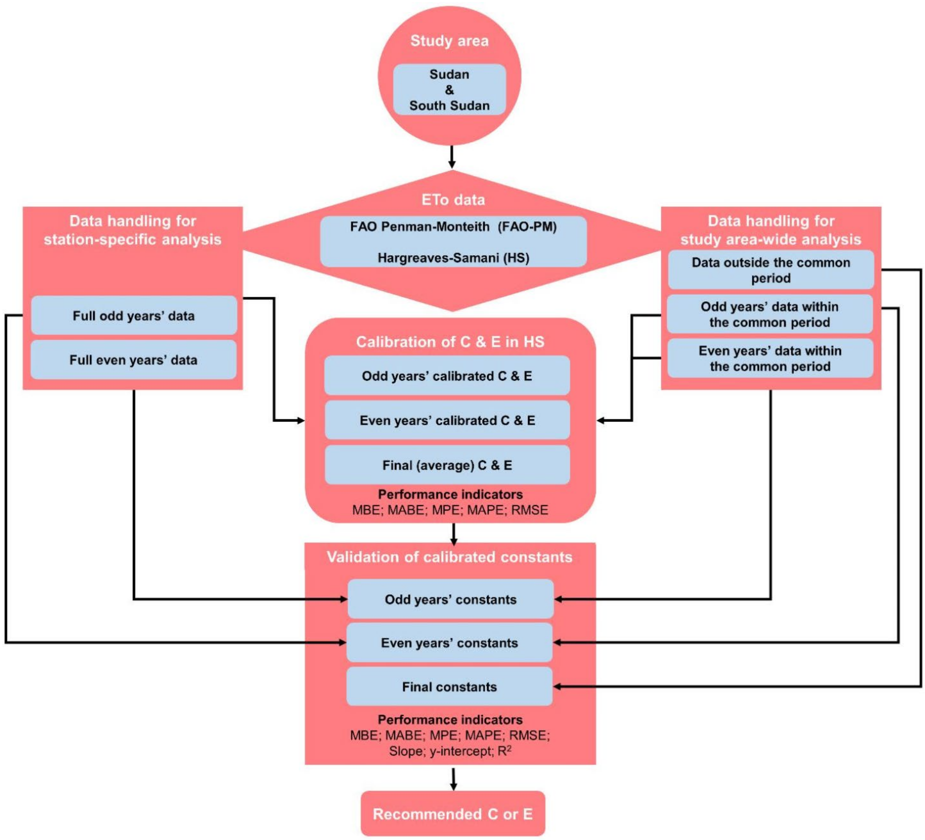

Fig. 1 Flowchart of the methodology

2.1 Data

A detailed description and source of the data used are given in the Supplementary Materials. This study used two monthly ETo datasets obtained using FAO-PM and HS following Equations (1) and (2) as per Allen et al. (1998) and Hargreaves and Samani (1985), respectively.

$$\mathrm{FAO-PM\ ETo} = \frac{0.408\triangle\left(\mathrm{R_n}-\mathrm{G}\right)+\gamma\frac{900}{\mathrm{T_m}+273}\mathrm{U_2}\left(\mathrm{e_s}-\mathrm{e_a}\right)}{\triangle+\gamma\left(1+0.34\mathrm{U_2}\right)} \tag{1}$$

where FAO-PM ETo is the ETo estimated by FAO-PM (mm $\mathrm{day^{-1}}$), R_n is the net radiation at the crop surface (MJ $\mathrm{m^{-2}\ day^{-1}}$), G is the soil heat flux density (MJ $\mathrm{m^{-2}\ day^{-1}}$), T_m is the mean daily air temperature at 2 m height above the ground (°C), U_2 is the wind speed at 2 m height above the ground (m $\mathrm{s^{-1}}$), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), $e_s - e_a$ is the saturation vapor pressure deficit (kPa), Δ is the slope of the vapor pressure curve (kPa $\mathrm{°C^{-1}}$), and γ is the psychrometric constant (kPa $\mathrm{°C^{-1}}$). The details for calculating these elements are provided in the Supplementary Material.

$$\text{HS ETo} = 0.0023 \times R_a\,(T_m + 17.8) \times (T_x - T_n)^{0.50} \quad (2)$$

where HS ETo is the ETo estimated using HS (mm day^{-1}), R_a is the extraterrestrial radiation in the same units of water evaporation (mm day^{-1}), T_m, T_x and T_n are the mean, maximum and minimum air temperatures, respectively, in °C. The term ($T_x - T_n$) defines the diurnal temperature range.

2.2 Data Handling for Calibration and Validation

Using the same dataset for calibration and validation of a model might lead to unreliable results as the model is not tested on different data during the two processes (Feng et al. 2017). For a more realistic evaluation, a long time series of data is recommended to provide a comprehensive picture of climate variability and allow separating the data into multiple sets (Er-Raki et al. 2010). Data splitting for calibration and validation of hydrological models has become a common technique and has many advantages (Yang et al. 2022). For example, it allows assessing the performance of the model on a different set of data that can help identifying any biases or overfitting during the calibration process. It also helps detect any temporal patterns in the data that the model may not have captured. Therefore, the present study followed this technique to handling the available datasets during the calibration and validation processes of the HS coefficient and overall exponent. We took the advantage of the long time series employed herein into consideration to divide the data into subsets, viz. two for the station-specific analysis and three for the study area-wide monthly analysis. In the former analysis, the full available dataset for each station was considered independently in odd years' or even years' data. Here, the length of data for either subset ranged from 11 to 25 years. In the latter analysis, the three sets included odd and even years' data of the common data period (1968–1984) among all the stations as well as data lying outside the common period. The time series thus spanned 8, 9 and 5–33 years, respectively. This dimension of data splitting has not been handled by the previous studies. These studies generally used traditional successive period-blocks of datasets that consider the calibration and validation processes with, for example, half the dataset before and the other half after. Such a dimension thus ensures that both processes involve the full range of climate variability encountered over the study period to explore possible variation and dependence on time in the results.

Based on the above data splits, two station-specific and three study area-wide strategies were adopted in the calibration and validation processes. In the station-specific analysis, the first strategy considered odd years' data for calibration and even years' data for verification. The opposite was practiced in the other strategy, i.e., data for even (odd) years were used for calibration (validation). Thus, the data size for odd or even years were composed of 132 records (11 years × 12 months) to 300 records (25 years × 12 months). The three strategies adopted in the study area-wide analysis were as follows. In the first one, the odd years' data (Data size: 8 years × 12 stations = 96 records) were used for calibration while the even years' data (Data size: 9 years × 12 stations = 108 records) for validation. Exchanging the even (odd) years' data for calibration (validation) was implemented in the second strategy. In the third one, the data outside the common period were exploited to validate the final calibrated monthly constants (average constants for odd and even years) station by station. This way, the data size for each month was 5–33 years depending on the given station. The purpose of the station-specific and the study area-wide analyses was to evaluate the performance of the adjusted HS across diverse climates (spatial analysis) and seasons (temporal analysis), respectively. These analyses ensure a comprehensive assessment of the HS model's performance in terms of both point (station) and spatial scale (study area-wide). If, for example, a geographical pattern of the results is detected across the study area, it will further help interpolate and extrapolate the calibrated constants for data scarce regions.

2.3 Performance Indicators

To assess the performance of the HS during the calibration and validation processes, several indicators were considered simultaneously. The scatter plot of FAO-PM versus HS ETo was used to observe the linear regression fit against the 1:1 line. The best performance of HS was achieved if the linear equation gave a y-intercept of zero, a slope of 1.0 and a determination coefficient, R^2, of 1.0. Other performance indicators, namely Mean Bias Error (MBE), Mean Absolute Bias Error (MABE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), were also used. Using multiple evaluation indicators is a common practice in literature. For instance, Zhu et al. (2019) used the slope, R^2, MABE and RMSE as measures for the performance evaluation of HS. Comparison of different model efficiency criteria was also emphasized by Krause et al. (2005) and Rahimikhoob et al. (2020).

2.4 Calibration and Validation Processes

Using iterations, HS was calibrated to tune the overall exponent E in Equation (3) and the coefficient C in Equation (4).

$$\mathrm{HS\ ETo} = \left[0.0023 \times \mathrm{R_a}\left(\mathrm{Tm} + 17.8\right) \times \left(\mathrm{Tx} - \mathrm{Tn}\right)^{0.50}\right]^{\mathrm{E}} \tag{3}$$

$$\mathrm{HS\ ETo} = \mathrm{C} \times \mathrm{R_a}\left(\mathrm{Tm} + 17.8\right) \times \left(\mathrm{Tx} - \mathrm{Tn}\right)^{0.50} \tag{4}$$

As indicated in the original HS (Equation (2)), C and E take values of 0.0023 and 1.0, respectively. The values of C and E were increased during the calibration process if HS ETo underestimated the FAO-PM ETo, and were decreased otherwise. Using odd years' data, C was tuned while keeping E constant, and vice versa until each of the performance indicators (i.e., MBE, MABE, MPE, MAPE and RMSE) reduced to its lowest possible magnitude. Then, the mean of the values of C or E corresponding to those lowest error metrics was suggested as the optimal constant for the odd years. Next, these optimal C and E constants were validated using the even years' dataset. Similarly, the original C and E values were calibrated using the even years' data. The averages of the optimal constants emerging from the odd and even years' datasets were eventually considered as the final calibrated constants. The above procedure was implemented in both the station-specific and the study area-wide (month-specific) analyses. An additional station-by-station validation of the final monthly constants for the study area-wide analysis was carried out using the data falling outside the common period.

To recommend the outperforming constant, i.e., either C or E, for each station and month, the five error metrics were compared with those relating to the validated C and E. In doing so, the absolute values of MBE and MPE were taken into account. Firstly, we counted the number of error indicators out of five favouring C or E. Then, the superior constant was identified as the higher score between C and E.

3 Results

Deviation of HS versus FAO-PM ETo regression line from 1:1 line using the original odd and even years' data is quite evident. The station-specific analysis (Fig. S2) clearly shows the tendency of HS to underestimate ETo at Port Sudan and Dongola in the hyper-arid zone and to overestimate it elsewhere. Also noticeable is that the HS efficiency declines southward from the hyper-arid to the dry sub-humid region. As for the study area-wide monthly analysis, Fig. S3 indicates predominant overestimation by HS. However, the model performs better in the rainy season (June-August) compared to the other parts of the year.

3.1 Calibration of the HS Constants

The analysis of the station-by-station odd and even years' data shows comparable calibrated C and E values (Fig. 2). Figure 2a shows higher C and E than the original HS values at the two hyper-arid stations but lower values elsewhere in the study area. To adjust the underestimation at Port Sudan and Dongola, C was thus increased to 0.00238 and 0.00247, respectively. Alternatively, independent calibration of E to 1.018 and 1.035 for the respective stations was required. In contrast, adjustment of the overestimation elsewhere was achieved by lowering the original C or E value to 0.00176–0.00226 or 0.842–0.990, respectively, depending on the given station. These modified constants increase linearly with latitude from the dry sub-humid to the hyper-arid region, as shown in Fig. 2b for the C and Fig. 2c for the E.

Figure 3 for the study area-wide analysis shows lower calibrated C and E than the original values throughout the year. The annual cycle of the optimal calibrated constants displays variations in the magnitudes. The C and E peak in the wet (June-September) and dry (December-March) seasons, but to a lower magnitude in the latter season. Conversely, they drop during the hottest months (April and May). Sharper drop is observed in the transitional months (October and November) between the wet and the dry seasons. On average, the calibrated C and E range from 0.00197 in November to 0.00218 in July/August (Fig. 3a) and from 0.902 in November to 0.971 in June (Fig. 3b), respectively.

3.2 Validation of the Calibrated Constants

3.2.1 Station-Specific Validation

Comparing Fig. 4 with Fig. S2, it is noticeable that the HS estimates can be reliably improved. The gap between the regression line and 1:1 line is narrowed post calibration. These findings are more pronounced for Ed Damazin, El Gedaref and Malakal in the semi-arid region and El Fasher and Kassala in the arid zone.

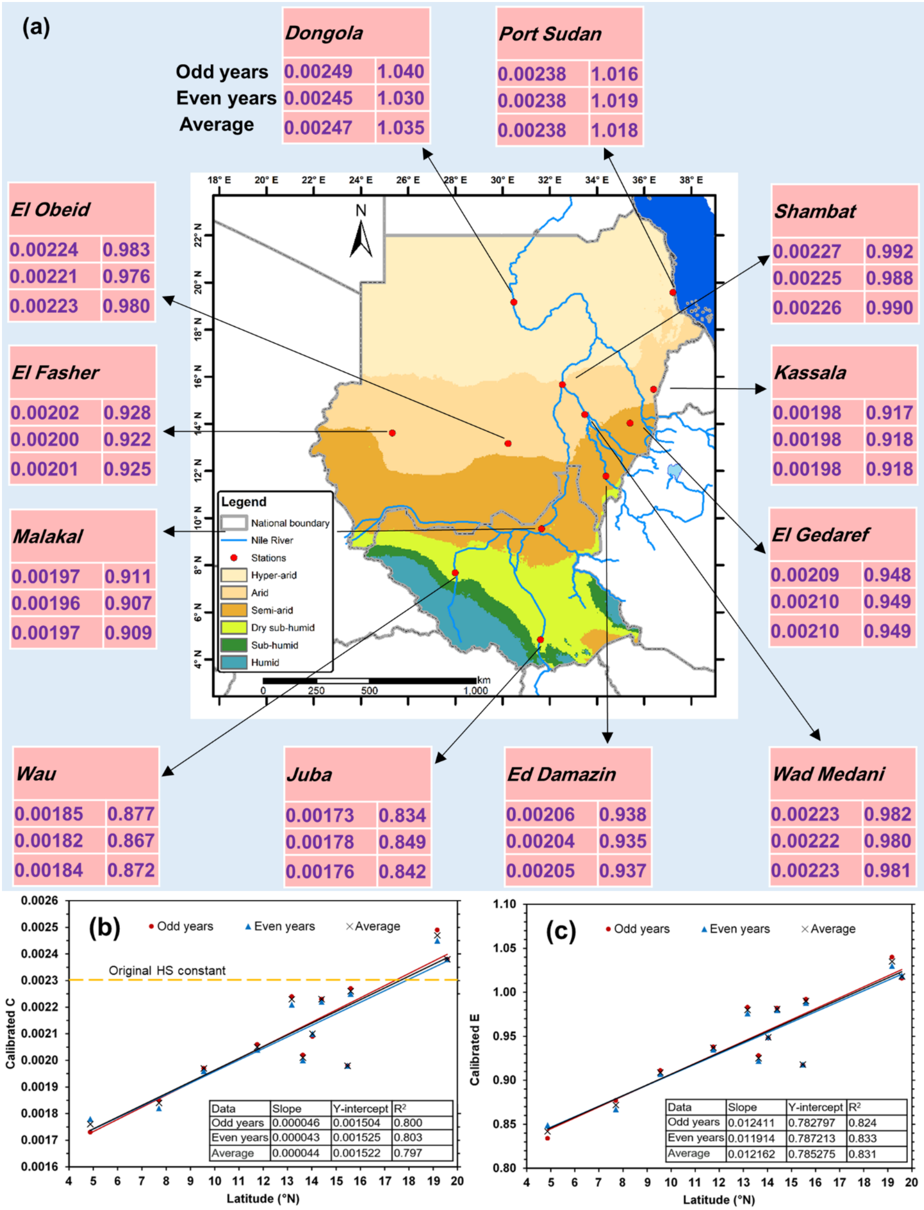

Fig. 2 Station-by-station optimal calibrated constants: (**a**) C and E values entered left and right in the tables, respectively, (**b**) Constants C versus the latitudes of the stations and (**c**) Constants E versus the latitudes of the stations. All regression coefficients and correlation factors are significant at ≤0.00009

Figure S4 explores the performance of the adjusted constants by comparing the error metrics before and after the calibration using the odd and even years' data exchangeably. In general, the errors show considerable reduction in the magnitudes and change in signs depending on the given station. MBE and MPE exhibit both underestimation and overesti-

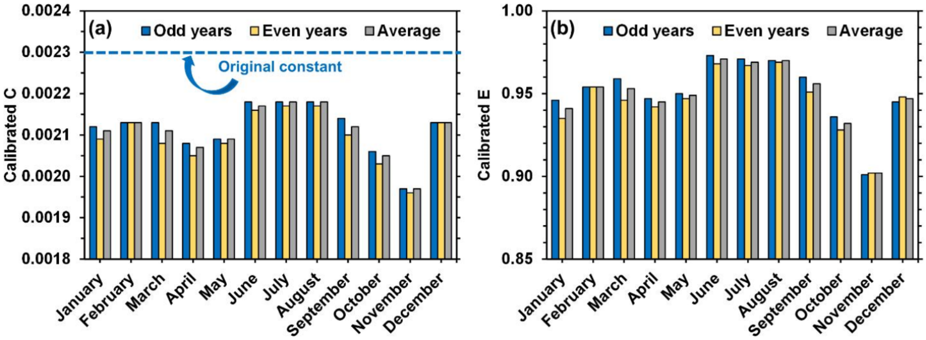

Fig. 3 Month-by-month optimal calibrated constants based on the study area-wide analysis: (**a**) C and (**b**) E

mation in each climatic zone rather than the original underestimation in the hyper-arid zone and overestimation elsewhere. On average, the MBE narrowed to −0.06-0.01 and −0.07-0.01 mm/day instead of −0.51-1.29 mm/day when using the calibrated C and E, respectively. The MPE reduced from −7.7-31.4% to −0.8-0.8 and −1.6-0.9%, respectively.

3.2.2 Study Area-Wide Validation

It is notable that the calibration effectively reduces the overestimates arising from the original HS (Fig. 5). The gap between the regression line and 1:1 line shrinks compared to its original counterpart in Fig. S3. This improvement is more apparent for April, May and October. The error metrics before and after correction are presented in Fig. S5 to measure the powerfulness of the calibration in improving the estimates. Most of the error metrics indicate largest improvement during the wettest months (June to August). For example, the annual cycle of the MBE and MPE reveals noticeable change in signs of error after adjustment. While the absolute MBE reduced tremendously from the original absolute values post validation of the even years' calibrated constants, the adjustment turned out to lead to a systematic underestimation (Fig. S5a). However, the validation of the odd years' calibrated constants resulted in both underestimation and overestimation (Fig. S5f). Based on the MPE, the validation results display both underestimation and overestimation instead of originally predominant overestimation (Figs. S5c and S5h). However, the magnitude of the new errors is much lower than that for the original errors. Using the calibrated C and E, the MBE narrowed on average from 0.28-0.66 to −0.11-0.00 and −0.12-0.02 mm/day, respectively. The MPE changed from 6.68-16.89 to −0.53-1.45 and −1.17-1.83%, respectively.

3.2.3 Additional Validation

By availing the full data outside the common period for each station, this section presents additional validation results of the calibrated monthly C and E. In this context, Fig. S6 shows the station-specific monthly MBE, which is categorized into positive, negative and overall MBE. The first two categories allow looking into the independent overestimates and underestimates, respectively. The results reveal different characteristics of the errors depending on the season. On one hand, the positive MBE indicates a tendency for the number of months with overestimation to decrease in the wet and/or dry season(s). Such a char-

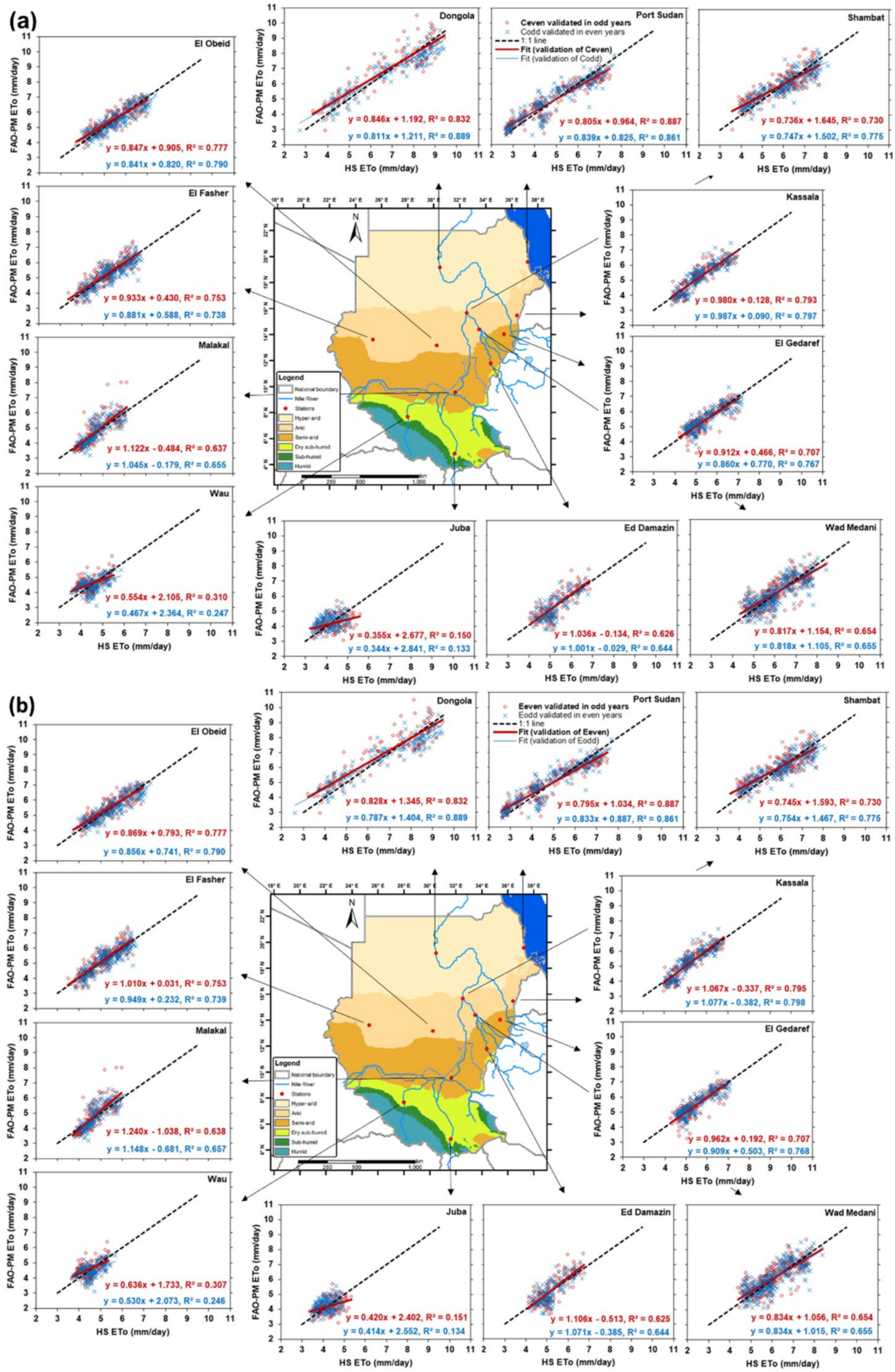

Fig. 4 Validation of adjusted HS ET_o for the stations using calibrated (**a**) C and (**b**) E

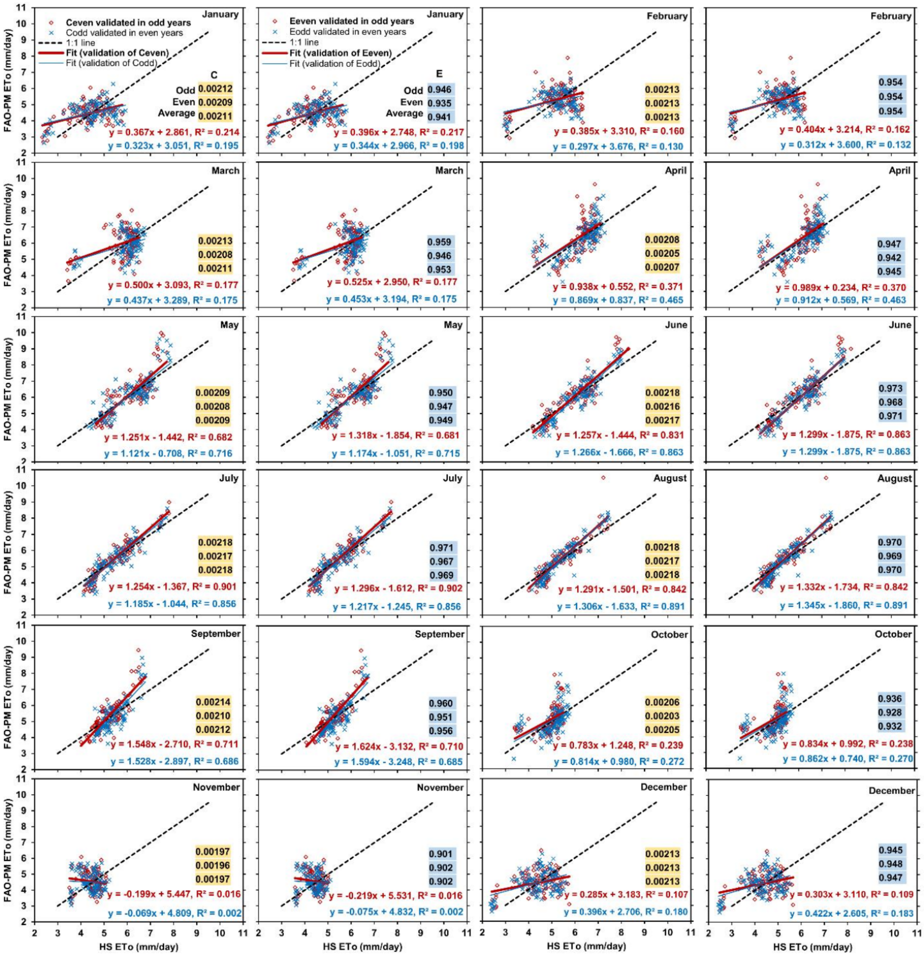

Fig. 5 Validation of adjusted HS ETo for the months using calibrated C (left) and E (right) based on the study area-wide analysis

acteristic is exemplified by Port Sudan, Dongola, Shambat, El Obeid and Ed Damazin. On the other hand, the negative MBE shows an increase in the number of months with underestimation. This result is noted for the wet season at Port Sudan and Dongola, the hot and wet seasons at El Gedaref and Ed Damazin and the hot and dry seasons at Kassala and El Fasher. It is worth noting here that Port Sudan at the coastline has distinct timing of the wet season compared to the inland stations. As for the third category (i.e., the overall MBE), the correction shows both overestimation and underestimation rather than the systematic overestimation characterizing the semi-arid stations. Conversely, it shows a turn from a combination of overestimates and underestimates to only underestimates at Port Sudan and Dongola in the hyper-arid region and at Shambat, Wad Medani and El Obeid in the arid region. It can be observed that the original HS may not require calibration at these five stations given the small errors in Fig. S4. Another observation is that overestimation still increases south of latitude 12° despite improved estimates. Using the final C and E, the overall MBE for the 12 stations changed from −0.71-2.17 mm/day to −1.35-1.70 and −1.37-1.66 mm/day, respectively. Excluding the stations that may not require calibration of HS, the overall MBE altered from 0.01-2.17 to −0.30-1.70 and −0.33-1.66 mm/day, respectively.

3.2.4 Recommended Constant

Given the variation in the results emerging between the two calibrated constants in reducing the errors, it is herein suggested that either C or E be adjusted in the original HS. Table S2 gives the best performing constant for both the stations and the entire study area. The calibrated C is outperforming at Port Sudan and Dongola in the hyper-arid region, Kassala in the arid zone and Ed Damazin and Malakal in the semi-arid region. Calibration of E is favoured for Shambat, Wad Medani, El Fasher and El Obeid in the arid zone, El Gedaref in the semi-arid zone and Wau and Juba in the dry sub-humid zone. Study area-wide, C is more suitable for the peak of the hot season (April and May) and for the wet season (June to October). A better result is obtainable using the proposed E values for the dry season (December to February), at the beginning of the hot season (March) and for the transitional month (November) between the wet and dry seasons.

4 Discussion

4.1 Implications of Data Splitting and Exchange on the Results

The results described in the previous section indicate that use of the approach of splitting and exchanging odd and even years' data in the calibration and validation processes has some implications. This approach, on one hand, shows appreciable variation in the results emerging between the two datasets, depending on the geographical location and the associated climate (Fig. 4) as well as the season of the year (Fig. 5). On the other hand, invariability or slight variation in the results can occur while calibrating the constants (Figs. 2 and 3) and using mean indicators of errors (Figs. S4 and S5). It is obvious that the use of mean errors masks the variations in performance between the two data splits as revealed in the scatter plots. This observation indicates further that less chance is to be expected in capturing the full range of climate during an era of changing climate. Thus, using the data for calibration and validation based on the traditional two block periods or windows of continuous years may involve bias and subsequent misinterpretation of results. Such a bias is likely if these two block-periods happened to cover a shift of climate from wet to dry or from cool to hot conditions and vice versa.

4.2 Relevance of the Present Results to Water Management

In Sudan and South Sudan, the inputs required to apply FAO-PM are very limited. The present study draws information of direct and practical relevance to active water management in the two countries. In view of the dependence of the calibrated values on latitude, interpolation and extrapolation of C and E at any location within the study region is possible through Fig. 2b and c, respectively, and the corresponding formulae. Both countries together encompass the largest spread of the Nile River basin and its tributaries. South Sudan embraces one of the largest wetlands in Africa, i.e. the Sudd region that extends over permanent and seasonal swampy area of 30,000 to 40,000 km^2, but for which hydro-meteorological data, including evaporation, are very scanty (Mohamed et al. 2006). It is estimated that 10% of the total Nile water is lost to evaporation and overspilling in this huge swampy area (Noordwijk 1984). The economy of both countries is reliant on agriculture. However, they are infamous for severe drought episodes (Elagib and Elhag 2011), resulting in decline of yield (Elagib et al. 2019) and occasions of famine (Maxwell et al. 2020). Sudan encompasses the vastest irrigated croplands in Sub-Saharan Africa (Mahgoub 2014), but also suffers poor management of irrigation water (Guvele and Featherstone 2001). These issues hence render the results of the present study of practical implications. The relevance relates to improving the understanding of the components of the hydrological cycle, drought assessment and agricultural water management.

4.3 Comparison with Previous Studies Worldwide

We have shown that the default C and E values had to be lowered to reduce the overestimation at the inland stations, except at Dongola. Conversely, both constants were increased to modify the underestimation at the coastal station, i.e. Port Sudan. Our findings align with those obtained by other researchers. For example, Jabloun and Sahli (2008) recognized a tendency toward a systematic overestimation of HS ETo versus FAO-PM ETo in inland areas and an underestimation in coastal areas in Tunisia. For China, Zhu et al. (2019) had to increase the value of C to correct the underestimation at coastal stations, and to decrease it in order to moderate the overestimation at inland stations.

In this study, the systematic overestimation observed at the arid and semi-arid stations required lowering the C and E values. However, this finding contrasts studies carried out in Iran. These studies suggested tendency for an underestimation exhibited by the original HS. For instance, the common 0.0023 value in HS was increased to enhance the estimates against FAO-PM ETo under arid and semi-arid climates (Fooladmand and Haghighat 2007; Tabari and Talaee 2011).

It is noted that the original HS manifests large overestimates of ETo at the more humid stations (Wau and Juba) in South Sudan (Fig. S2), particularly from October to April as confirmed by the study area-wide analysis (Fig. S3). Such a result matches some results of previous studies. Trajkovic (2007) indicated an overestimation of ETo by HS in a high humid region of the Western Balkans, South East Europe. Using data from 19 meteorological stations of Sichuan basin, southwest China, Feng et al. (2017) also found that HS largely overestimated ETo in high relative humidity condition reaching 79%. Temesgen et al. (2005) attributed the possible overestimation of HS ETo at two humid stations (Lodi West and Novato) in California to high humidity. Thus, higher humidity condition can lead to higher values of HS ETo compared to FAO-PM ETo and to low correlations between FAO-PM and HS ETo values, even after validation of adjusted HS ETo for the respective stations (Fig. 4) and the months (Fig. 5). It is worth noting that South Sudan covers a large swampy area in which the relative humidity is 50–80% (Mohamed et al. 2006). During April to October, data on maximum relative humidity for these two stations (not shown) indicate a range of 70–100%.

In this study, the proposed constants for the stations are shown to be latitude-dependent. A gradient reveals from the too dry stations in the north to the more humid stations in the south. Such findings agree with the results reported by Zhu et al. (2019) for China. They found the constant C to decrease from the arid region towards the humid region using 838 meteorological stations. This match is very encouraging in light of only 12 meteorological stations covered herein.

Lowering constant C was necessary to adjust the overestimation of HS ETo noted for all the months of the year in Kashan, Iran (Heydari and Heydari 2014). Their findings showed higher calibrated C for the hot months than those obtained for the wet and dry months. While these results agree with ours in terms of HS deviation from the standard FAO-PM, they are entirely opposite to ours in the direction of the annual cycle of the calibrated constants.

The current findings confirm those obtained elsewhere for similar climates in relation to the wide ranges of the calibrated C values. We found herein 0.00176-0.00247 for the stations and 0.00197-0.00218 for the monthly study area-wide analyses. For instance, Heydari and Heydari (2014) obtained calibrated C values of 0.0013-0.0043 (monthly) and 0.0018-0.0037 (annual) for arid and semi-arid stations in central Iran. Results for Iran also showed monthly calibrated C value of 0.0016-0.0038 (Mehdizadeh et al. 2017). The constant C was corrected to 0.0025-0.0067 for many stations spread across 10 agro-climatic zones in India (Niranjan and Nandagiri 2021).

The above discussion points out the extent of dissimilarity of the HS performance that can reveal in regions with comparable climates to ours in spite of somewhat similarity as well.

5 Conclusions

The main challenge to applying the standard method, i.e., FAO-PM, for estimating ETo is the limitation of weather data, especially in the developing world. Although HS is not fully effective in estimating ETo, it may provide promising estimates if a sensible correction is carried out. This paper has introduced new dimensions to the calibration and validation of the HS constants. While the data used in this study were obtained from only 12 meteorological stations across Sudan and South Sudan, they still represent vast hydroclimate environments. The analysis was performed not only on a classic station basis, but also on monthly basis for the entire study area using the 12 stations' data. Additional novel dimension was the split of the available data into odd and even years' datasets to exchange them between the calibration and validation processes. This way, each process involved the full range of climate variability within the time series. The main conclusions drawn from the present study are as follows:

- Station-based calibrated C and E ranged from 0.00176 to 0.00247 and from 0.842 to 1.035, respectively. The original values of C and E were increased to reduce the error emerging from the underestimation in the hyper-arid zone. Conversely, they were decreased to moderate the overestimation in the other climate zones. These constants were found to vary linearly with latitude, increasing from the dry sub-humid zone to the hyper-arid zone.
- Based on merging the data for the 12 stations, the calibration resulted in C values of 0.00197-0.00218 and E values of 0.902-0.971. The evident overestimates across the entire study area were adjusted by replacing the original values of C and E by lower ones. Least calibration was required for the wettest months inland, followed by the dry/cool

months. In contrary, calibration was largest for the transitional months between the wet and dry/cool seasons, followed by the hottest months inland.

- Instead of the systematic underestimation in the hyper-arid zone and overestimation in the other climatic regions, the calibration lead to both underestimation and overestimation in each climatic zone.
- Adjustment of the C was found more appropriate for the hyper-arid and semi-arid zones in addition to the hot and wet months. Calibration of the E was more suitable for the arid and dry sub-humid zones as well as the dry/cool months.

There are various implications that can be laid for science and application based on the above results. The latitude dependence of adjusted C and E offers interpolation and extrapolation of the constants at any location within the huge area covered by the two countries. Both the match and mismatch of the calibrated C and E with previous findings for similar climates open venues for similar studies elsewhere. Splitting and exchanging odd and even years' data between the calibration and validation processes indicate paramount implications for results and the way these results are interpreted, especially in an era involving shift of climate. In overall, the outcome of this study contributes to accurately estimating ETo in such a data-limited region in support of better planning and decision-making in water management.

Considering the inherent scarcity of meteorological stations as a major limitation of the current study, one recommendation to offer is to validate the adjusted HS using more meteorological stations within the two countries when available in the future. This attempt will offer further examination of the transferability of the latitude-dependent C and E regression formulae of Fig. 2. Another recommendation for further research is to apply the proposed approach in other regions to revisit the results obtained in these regions based on data splitting.

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Data Availability The FAO-PM ETo and HS ETo data supporting the finding of this study are available upon reasonable request from the corresponding author [N.A. Elagib]. However, the original meteorological data used to calculate FAO-PM ETo and HS ETo are owned by and were acquired from Sudan Meteorological Authority (SMA). Requests should therefore be made directly to SMA.

Declarations

Conflict of Interest The authors declare that they have no known conflict interests.

Ethical Approval Not applicable.

Consent to Participate All authors consented to participate.

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