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Comparative assessment of different reference evapotranspiration models towards a fit calibration for arid and semi-arid areas

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ABSTRACT

The enhancement of water efficiency requires controlling the high demand for irrigated agriculture which depends on improving the capabilities to accurately simulate the water cycle and its components. Among these, evapotranspiration is widely studied to estimate reference evapotranspiration (ET0) but the performance and accuracy of the estimates vary. Moreover, these estimates require some hardly available or misrepresentative meteorological data which lead, mainly in arid and semi-arid areas, to errors and inaccuracies. Here, ET0 of five empirical temperature-based estimates are compared to the standard FAO Penman-Monteith estimate (ET0-PM) under the representative and wide-ranging settings of 22 weather stations of Morocco. We found a significant positive correlation between ET0-PM and solar radiation, average and maximum air temperatures. We have determined that the Dorji estimate shows relatively better precision and stability while it requires advanced calibration to accommodate arid and semi-arid conditions. After hundreds of calibration repetitions, we concluded a new estimate (ET0-Hadria) which demonstrates an overall improvement in the quality and precision of ET0 assessment, mainly in flat areas. This estimate improved the precision and enhanced the precision in almost 68% of the stations. This simple calibrated estimate is an accurate, improved, and transferable tool achieved through a precise methodical process of selection and configuration.

1. Introduction

In spite the succession of World Food Summits in recent decades, it is unfortunate that the achievement of the critical global goal of eradicating hunger remains unattainable (Creegan and Flynn, 2020; Otekunrin et al., 2019; Swaminathan, 2010). Furthermore, the scarcity of freshwater is increasingly perceived as a global risk that will substantially worsen under the impact of climate change, affecting natural biodiversity and the welfare of billions of people around the world (Gosling and Arnell, 2016; Mekonnen and Hoekstra, 2016; Meng et al., 2016). The strong and complex interlinkages among the United Nations Sustainable Development Goals mean that the whole is endangered if one of the aforementioned goals cannot be achieved (Nilsson, 2016).

If this threat to the sustainable development of the global community is not enough, the current Covid-19 pandemic undoubtedly demonstrates the importance of ensuring the sovereignty of water and food for the security and stability of nations. The world is entering an uncharted territory that will trigger deep economic, health and behavioural mutations. COVID-19 forces national economies to slow to a near-halt and life is stripped down to its essentials; water and food first! (Cappelli and Cini, 2020; Erikson, 2020; McKee and Stuckler, 2020).

In this unprecedented severe context, the efficient management of water resources is the absolute priority. Still, enhancing water efficiency necessarily requires controlling the very high demand for irrigated agriculture, which accounts for more than 70% of global water use (Pastor et al., 2019; Turral et al., 2011). This definitely depends on improving the capabilities to accurately simulate the water cycle and its components. Among them, evapotranspiration is essential in water, energy, and carbon cycles, yet it remains one of the most difficult to measure and model at regional and basin scales (Lionboui et al., 2016; Liu et al., 2016; Singh et al., 2017; Talbot, 2019). Evapotranspiration phenomenon have been widely studied under different climate zones and land cover types worldwide and by using different methods from the simplest ones to the more complex systems. The main first works that studied this question where those of (Hargreaves and Samani (1985); Penman and Keen (1948)). Then, a multitude of models, has been
developed to estimate evapotranspiration from a minimum number of meteorological variables and recently from remotely sensed data. For example, Trajkovic (2007) compared Hargreaves to FAO Penman-Monteith model and Trajkovic and Kolakov (2009b) evaluated five reference evapotranspiration equations under humid Conditions in Western Balkans (South East Europe). On their side, Samaras et al. (2014) evaluated 18 potential evapotranspiration equations under different Mediterranean climates in Greece. In United States, Lu et al. (2005) compared six potential evapotranspiration methods under the southeastern United States climate while Djaman et al. (2019) evaluated Penman–Monteith and 34 other reference evapotranspiration methods under semi-arid dry climate of New Mexico. In China, Yang et al. (2016) evaluated eight evapotranspiration models under semi-arid and semi-humid areas. In Africa, Djaman et al. (2015) compared sixteen reference evapotranspiration equation under Sahelian conditions in the Senegal River Valley and Ndiiye et al. (2017) evaluated twenty models to estimate reference evapotranspiration in Burkina Faso. At global scale, many authors proposed methods to estimated evapotranspiration from meteorological data or remote sensing data (see for example: Anayah and Kaluarachchi, 2019); (Miralles et al., 2011); (Wang and Liang, 2008); (Senay et al., 2020)).

Actually, reference evapotranspiration is defined as the maximum amount of water, which can be evaporated or transpired from a vegetated area, regardless of the amount of available water in the soil-plants system (Allen et al., 1998; Lu et al., 2005). It is assessed based on several estimates that vary in complexity and accuracy which, however, depends on the representativeness of each estimate with regard to the topographic, geographic and climatic conditions of a given area of interest (Feng et al., 2017; Jensen et al., 1990).

There are several estimates for reference evapotranspiration assessment but their performance and accuracy vary. In the literature, Penman-Monteith model is highly recommended and is assumed to be the most accurate. However, this method requires a lot of hardly available meteorological data which could be a real hindrance (Feng et al., 2017; Gocic and Trajkovic, 2010). Yet, the standardised FAO Penman–Monteith method (Allen et al., 1998) is then proposed and recommended as the standard method for ET0 assessment, even if, in some weather conditions, it can lead to errors as high as 30% (Widmoser, 2009). In addition, some specific parameters of this estimate are still difficult to obtain in many countries, mainly of the South, which constitutes an obstacle to its application (Gocic and Trajkovic, 2010).

The spatiotemporal availability and the representativeness of the required data is also a fundamental determinant of the choice of the estimate. Consequently, the use of simple empirical ones requiring fewer data is highly recommended, especially when there is a lack of data, as in the MENA region (Djaman et al., 2015, 2019; Er-Raki et al., 2010; Hadria et al., 2018, Mahmoud and Gan, 2019; Ning et al., 2018; Trajkovic and Kolakovic, 2009a).

In this context, a multitude of simpler empirical methods, more adapted for practical use, has been developed to estimate ET0 from a minimum number of climatic variables. In general, there are three classes of estimates: (i) air temperature-based, (ii) radiation-based, and (iii) mass transfer based. After its local calibration, the first class provides good approximations of ET0 and has the advantage of being widely studied (Bicalho et al., 2016; Djaman et al., 2015, 2019; Trajkovic, 2007). Often, these estimates are applied in areas where the climatic and agronomic conditions are very different from the humid or even Nordic settings in which they were developed and tested. Therefore, to avoid any exaggeration or inaccuracy, it is imperative to put them through validity comparisons before applying them in different, especially arid, areas such as North Africa and the Middle East (MENA) and large sectors around the Mediterranean (Salhi, 2008; Tapias and Salgot, 2006).

In Morocco, the spatial extension of the bioclimatic stages, the ideal geographical position, the geomorphological diversity, the variability of the arid settings and the data availability hardness make it typical and representative of the MENA region to compare different reference evapotranspiration models towards a fit calibration for these arid and semi-arid areas (Benabdellouahab et al., 2019; Hadria et al., 2019; Mokhtari et al., 2014).

In this paper, ET0 is assessed based on a comparison of five of the simplest empirical temperature-based estimates with the standard FAO Penman–Monteith estimate. Subsequently, the finest model was selected for an improved parameterization and better calibration for the arid and semi-arid conditions of the Moroccan context.

This parameterization will provide an improved model adapted to the specificities of this area which will allow managers and stakeholders to better understand the spatiotemporal evapotranspiration irregularity in order to anticipate appropriate strategies for water and agriculture management (Benabdellouahab et al., 2020; Salhi et al., 2020a, 2020b). This calibrated model is an essential basic tool that must be at the same
2. Materials and methods

2.1. Study area and data

The study area is central and northern Morocco (365,300 km²) where all the bioclimatic stages and agro-ecological zones of the country are included (Fig. 1). It is characterized by strong longitudinal and latitudinal climatological gradients. The average annual air temperature varies between 12 and 14 °C in winter and between 22 and 24 °C in summer. The average annual rainfall varies from about 150 mm, in the southern desert, up to over 1000 mm in the northern Rif and the central Atlas mountains.

Based on the international Köppen-Geiger climate classification, six climate zones stand out in the study area: Bsh (Arid-Steppe-hot arid), Bsk (Arid-Steppe-Cold arid), Bwh (Arid-Desert- hot arid), Csa (Hot-summer Mediterranean climate), BWk (Cold desert climate) and CSb (Warm-summer Mediterranean climate) (Hadria et al., 2019).

The main meteorological parameters affecting evapotranspiration are solar radiation, air temperature, vapor pressure deficit and wind speed (Allen et al., 1998). In this study, solar radiation, air temperature, relative humidity and wind speed were obtained from abundant data collected from a network of 22 well-scattered automated weather stations in the study area. Data accuracy, quality and homogeneity are guaranteed by the National Institute for Agronomic Research of Morocco, manager of the aforementioned stations. These are representative of the territorial diversity of the country, dispersed from coastal plains to mountain peaks and from fertile agricultural areas to desert terrain (Fig. 1 and Table 1). The three components of air temperature (minimum, maximum and average), solar radiation, wind speed, and relative humidity were collected on a half-hour basis.

The entire database was constantly checked to make sure it did not contain any outliers or missing values. Thereafter, daily data was drawn from 23,838 records for all climate stations.

2.2. The standard FAO Penman–Monteith estimate

The well-known FAO Penman-Monteith reference evapotranspiration (ET₀−PM) is a standard estimate, recommended for daily ET₀ (mm/day), which can be assessed as follows (Allen et al., 1998):

\[
ET_0^{\text{PM}} = \frac{0.408 \Delta (R_n - G) + \frac{900}{T_{avg} U_2} (e_{\text{a}} - e_{d})}{\Delta + \frac{900}{1 + 0.34 U_2}}
\]

Where \(R_n\) is the solar net radiation (MJ/m²/day), \(G\) is the soil heat flux in (MJ/m²/day), \(T_{avg}\) is the average air temperature in (°C), \(U_2\) is the average wind speed measured at 2m height in (m/sec), \((e_{\text{a}} - e_{d})\) is the vapour pressure deficit in (kPa), \(\Delta\) is the slope of the vapour pressure curve (kPa/degC), \(\gamma\) is the psychrometric constant (kPa/°C) which is equal to 0.66. The vapour pressure and the slope of vapour pressure were calculated based following the formulas suggested by Allen et al. (1998).

2.3. The five ET₀ temperature-based estimates

The five other ET₀ studied temperature-based estimates were chosen for their simplicity, accuracy and for the availability of the required air temperature parameters which are, generally, directly measured in weather stations or indirectly retrieved from remote sensing data (Fabiola Flores and Mario Lillo, 2010; Hadria et al., 2019; Hadria et al., 2018; Mildrexler et al., 2011; Vancutsem et al., 2010). These five estimates are originated from the pioneer Hargreaves equation and are as follows:

- Hargreaves and Samani estimate (Hargreaves and Samani, 1985):

\[
ET_0^{\text{HSG}} = 0.0408 \times 0.0023 \times (T_{avg} + 17.8) \times (T_{max} - T_{min}) \times 0.5 \times Ra
\]

- Ravazzani estimate (Ravazzani et al., 2012):

\[
ET_0^{\text{Rav}} = 0.408 \times 0.0023 \times (0.817 + 0.00022 \times z) \times (T_{avg} + 17.8) \times (T_{max} - T_{min}) \times 0.5 \times Ra
\]
- Berti estimate (Berti et al., 2014)

\[
ET_0^{\text{Berti}} = 0.408 \times 0.00193 \times (T_{avg} + 17.8) \times (T_{max} - T_{min}) \times 0.517 \times Ra
\] (4)

- Trajkovic estimate (Trajkovic, 2007)

\[
ET_0^{\text{Trajkovic}} = 0.408 \times 0.0023 \times (T_{avg} + 17.8) \times (T_{max} - T_{min}) \times 0.424 \times Ra
\] (5)

- Dorji estimate (Dorji et al., 2016)

\[
ET_0^{\text{Dorji}} = 0.408 \times 0.002 \times (T_{avg} + 33.9) \times (T_{max} - T_{min}) \times 0.296 \times Ra
\] (6)

Where \(T_{min}\), \(T_{max}\) and \(T_{avg}\) are the daily minimum, maximum and average air temperature, respectively (°C); \(Ra\) is the daily atmospheric radiation (MJ/m²/day) calculated using the standard astrophysics equations proposed by Allen et al. (1998). The variable \(z\) in Ravazzani estimate (equation (3)) is the station elevation above sea level (m).

The results of these estimates were compared with those of their \(ET_0^{\text{PM}}\) counterparts using the following linear regression analysis formula:

\[
ET_0^{\text{est}(i)} = a \times ET_0^{\text{PM}(i)} + b
\] (7)

Where \(ET_0^{\text{est}(i)}\) is the reference evapotranspiration assessed after an empirical estimate and \(ET_0^{\text{PM}(i)}\) is its counterparts assessed after the FAO Penman-Monteith estimate at the day \(i\) for each station. The regression coefficients ‘\(a\)’ and ‘\(b\)’ denote the slope and the intercept of the regression line, respectively.

The accuracy between the \(ET_0\) of the five estimates and the FAO Penman-Monteith estimate was assessed using three statistical indices: the coefficient of determination \((R^2)\), the normalized root mean square error (nRMSE) and the percentage error (PE) as follows:

\[
R^2 = \frac{\sum_{i=1}^{n} (\hat{ET}_0 - ET_0)(i) - (\hat{ET}_0 - ET_0)(i)}{\sum_{i=1}^{n} (\hat{ET}_0(i) - \hat{ET}_0)(i))^2} + \sum_{i=1}^{n} (\hat{ET}_0(i) - \hat{ET}_0)(i))^2}
\] (8)

\[
n\text{RMSE} = \frac{1}{\hat{ET}_0} \sqrt{\frac{1}{n} \sum_{i=1}^{n} (ET_0(i) - \hat{ET}_0)(i))^2}
\] (9)

\[
\text{PE} = \frac{|ET_0(i) - \hat{ET}_0(i)|}{ET_0(i)} \times 100
\] (10)

Fig. 2. The relationships between daily \(ET_0^{\text{PM}}\) and the key climate variables measured the 22 studied stations.
Where $ET_{0\text{emp}}$ and $ET_{0\text{FAO}}$ are the average of the $ET_0$ assessed after an empirical estimate and its counterparts assessed after the FAO Penman-Monteith estimate, respectively, and $n$ is the number of the studied days (Records number in Table 1). A perfect agreement between $ET_{0\text{emp}}$ and $ET_{0\text{FAO}}$ with no bias corresponds to $a = 1$, $b = 0$ mm/day, $R^2 = 1$, nRMSE = 0 and PE = 0.

2.4. Parameterisation of new model under Moroccan conditions

The five selected temperature-based estimates for assessment, comparison and accuracy evaluation, are originated from the following leading Hargreaves equation:

$$ET_0 = 0.408*\alpha*(T_{avg} + \beta)*(T_{max} - T_{min})^{3/2}*Ra$$ (11)

Where the parameters $\alpha$, $\beta$ and $\delta$ are often calibrated for each station.
In the literature, the value of $\alpha$ parameter oscillates generally around 0.002. In this paper, a new parameterization of the model described by equation (11) was proposed through calibrating the two parameters $\beta$ and $\delta$. To do this, 50% of the ET$_0$ data collected in half of the studied weather stations (eleven) was randomly selected for each calibration step. The parameters were iterated randomly until they match the best combination, which minimize errors between ET$_0$ estimated by calibrated model and ET$_0$-PM. The validation process was performed by evaluating the new parameterised model by using the data of the remaining half eleven stations. This operation was then repeated automatically a hundred times to verify the stability of $\beta$ and $\delta$ parameters' values. Finally, the average values of these parameters obtained from the hundred repetitions were used in the final suggested estimate and evaluated to ET$_0$-PM outputs at the spatial scale of the country.

### 3. Results and discussions

#### 3.1. Relationship between ET$_0$-PM and climate data

The daily ET$_0$-PM were compared with the measured climate data: solar radiation, air temperature, relative humidity and wind speed (Fig. 2). This comparison showed a good agreement between solar radiation, average and maximum air temperatures parameters, and ET$_0$.

| min | max | average | std |
|-----|-----|---------|-----|
| $\beta$ (°C) | 25.8 | 27.3 | 26.3 | 0.2 |
| $\delta$ | 0.390 | 0.417 | 0.397 | 0.003 |

The new (calibrated) parameters allowed to obtain hundred equations, which were designated ET$_0$-Hadria$_i$, described by the following equation.

(Berti et al., 2014; Dorji et al., 2016; Hargreaves and Samani, 1985; Ravazzani et al., 2012; Trajkovic, 2007). In the literature, the value of $\alpha$ parameter oscillates generally around 0.002. In this paper, a new parameterization of the model described by equation (11) was proposed through calibrating the two parameters $\beta$ and $\delta$. To do this, 50% of the ET$_0$ data collected in half of the studied weather stations (eleven) was randomly selected for each calibration step. The parameters were iterated randomly until they match the best combination, which minimize errors between ET$_0$ estimated by calibrated model and ET$_0$-PM. The validation process was performed by evaluating the new parameterised model by using the data of the remaining half eleven stations. This operation was then repeated automatically a hundred times to verify the stability of $\beta$ and $\delta$ parameters' values. Finally, the average values of these parameters obtained from the hundred repetitions were used in the final suggested estimate and evaluated to ET$_0$-PM outputs at the spatial scale of the country.

![Fig. 4. The relationships between the daily ET$_0$ values assessed by the five methods and ET$_0$-PM by mixing data of the 22 weather stations. Dashed blue line shows the (1:1) line while the solid red line corresponds to the regression line between ET$_0$ values assessed by the five methods and ET$_0$-PM. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)](image)

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![Table 3. The minimal, maximal, average and standard deviation values of calibrated parameter $\beta$ and $\delta$.](image)

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The new (calibrated) parameters allowed to obtain hundred equations, which were designated ET$_0$-Hadria$_i$, described by the following equation.

![Fig. 5. The average values of the slope (a), intercept (b), normalized root mean square error (nRMSE), coefficient of determination ($R^2$) and percentage error (PE) between the one hundred calibrated Hadria$_i$'s estimates and ET$_0$-PM for the one hundred groups of validation stations. PE was resized by a division of 100.](image)

Figure 5. The average values of the slope (a), intercept (b), normalized root mean square error (nRMSE), coefficient of determination ($R^2$) and percentage error (PE) between the one hundred calibrated Hadria$_i$'s estimates and ET$_0$-PM for the one hundred groups of validation stations. PE was resized by a division of 100.
radiation by (Djaman et al., 2019). The comparison between ET\(_{0-PM}\) and the minimum air temperature shows an R\(^2\) of 0.49 close to what it was obtained by Djaman et al. (2019) (R\(^2\) = 0.58). Finally, the agreements were poor when comparing ET\(_{0-PM}\) to the relative humidity and wind speed with an R\(^2\) of 0.21 and 0.18, respectively, in concordance with a similar study of Djaman et al. (2019).

From these comparisons, it was concluded that solar radiation and air temperature are the most important parameters affecting the reference evapotranspiration, hence the interest of selecting the temperature-based estimates for its assessment in this study.

### 3.2. Assessment of the five studied models

The previous five ET\(_0\) air temperature-based models (section 2.3) were compared to the FAO Penman-Monteith model at the station level according to the coefficient of determination (R\(^2\)), the normalized root mean square error (nRMSE) and the percentage error (PE) (Fig. 3). Values are displayed in ascending order of station elevation to reveal its effect on the accuracy of the studied models. In addition, Table 2 shows the minimum, maximum, average values and the standard deviation of the three previous statistical indicators.

The five studied models show good agreement with respect to the

|     | a     | b     | nRMSE | R\(^2\) | PE    |
|-----|-------|-------|-------|--------|-------|
| min | 0.71  | 0.66  | 0.22  | 0.87   | 6.60  |
| max | 0.86  | 0.84  | 0.29  | 0.90   | 16.36 |
| avg | 0.79  | 0.77  | 0.25  | 0.88   | 11.89 |
| std | 0.03  | 0.04  | 0.02  | 0.01   | 2.12  |

Fig. 6. Comparison between the original Dorji model and its calibration version (Hadria 2020) at the station level: a) Coefficient of determination (R\(^2\)), b) Normalized Root Mean Square Error (nRMSE) and c) Percentage Error (PE).
Fig. 7. 

Localization of the stations where \(ET_{0,\text{Hadria}}\) got better accuracy (green triangles) and those where it did not (red triangles). The numbers show the PE values for both estimates. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

### Table 5

| Station          | \(n\text{RMSE}\) | \(R^2\) | \(PE\) | \(n\text{RMSE}\) | \(R^2\) | \(PE\) |
|------------------|------------------|--------|--------|------------------|--------|--------|
| Alal Tazi        | 0.3              | 0.91   | 11.8   | 0.2              | 0.90   | 2.6    |
| Boukhalef        | 0.4              | 0.84   | 20.2   | 0.3              | 0.82   | 14.0   |
| El Menzeh        | 0.2              | 0.91   | 7.3    | 0.2              | 0.91   | 2.0    |
| Larache          | 0.2              | 0.90   | 3.9    | 0.2              | 0.87   | 4.8    |
| Nadir            | 0.2              | 0.92   | 4.4    | 0.2              | 0.92   | 4.3    |
| El Koudia        | 0.2              | 0.91   | 5.0    | 0.2              | 0.91   | 3.3    |
| Zemamra          | 0.3              | 0.86   | 7.7    | 0.2              | 0.86   | 2.7    |
| Sidi Elsadı      | 0.3              | 0.91   | 21.8   | 0.2              | 0.91   | 11.8   |
| Guerzif          | 0.2              | 0.91   | 1.6    | 0.2              | 0.89   | 11.6   |
| Douet            | 0.5              | 0.81   | 29.4   | 0.4              | 0.82   | 20.9   |
| Settat           | 0.4              | 0.85   | 29.8   | 0.3              | 0.85   | 20.3   |
| Merdouch          | 0.3              | 0.91   | 6.8    | 0.2              | 0.88   | 0.2    |
| Ain Taoujdate     | 0.2              | 0.90   | 2.8    | 0.3              | 0.89   | 16.0   |
| Marrakech        | 0.3              | 0.88   | 9.9    | 0.2              | 0.87   | 3.9    |
| Beni Mellal      | 0.2              | 0.93   | 3.9    | 0.3              | 0.93   | 19.7   |
| Tassaout         | 0.2              | 0.94   | 0.5    | 0.2              | 0.93   | 14.8   |
| Zagora           | 0.3              | 0.90   | 18.5   | 0.5              | 0.89   | 38.4   |
| Tinejdad         | 0.2              | 0.90   | 7.8    | 0.3              | 0.87   | 23.6   |
| Errachidia       | 0.2              | 0.93   | 11.8   | 0.3              | 0.91   | 28.6   |
| Boufarouch       | 0.3              | 0.87   | 18.6   | 0.3              | 0.86   | 8.3    |
| Laanaceur        | 0.3              | 0.92   | 14.3   | 0.2              | 0.92   | 3.9    |
| Marroucha        | 0.2              | 0.87   | 10.3   | 0.2              | 0.86   | 0.2    |

FAO Penman-Monteith model with \(R^2\) values between 0.80 and 0.94 (Fig. 3a). It is also observed that the precision of \(ET_0\) decreases on the contrary to the altitude, with the exception of the Dorji model (Fig. 3c). This is explained by the fact that this last method was obtained by calibrating the Hargreaves equation (Hargreaves and Samani, 1985) under the complex mountainous terrain of Bhutan, in the Himalayas (Dorji et al., 2016).

Even if the five models all come from that of Hargreaves and Samani equation, their accuracy depends closely on their calibration for the settings of a given study area; hence the importance of their advanced calibration before any application under the arid and semi-arid conditions.

The average values of the \(n\text{RMSE}\) vary between 0.25 and 0.40 with a standard deviation varying between 0.07 and 0.20 (Table 2). The PE values show that only the models of Dorji and Trajkovic give \(ET_0\) results with PE values below the 15% threshold suggested by Allen (1993) and Djaman et al. (2019). However, we observe that Dorji’s method is slightly more stable than Trajkovic’s one based on the standard deviation values (8.5 and 11.0, respectively).

Later, the same previous analysis was performed based on the all-meteorological data of the 22 studied stations mixed together. The comparison between the daily \(ET_0\) values estimated by the five models with \(ET_{0,PM}\) shows, in general, a good agreement (Fig. 4). However, the analysis of the values of the statistical indices indicates that the estimates of Dorji and Trajkovic methods were more precise compared to the other three. Subsequently, it was decided to select Dorji’s estimate for advanced calibration based on its good agreement with \(ET_{0,PM}\) and its stability.

### 3.3. Parameterization results of new model under Moroccan conditions

For the one hundred calibration repetitions previously described in section 2.4, one hundred couple of the parameters \(\beta\) and \(\delta\) of equation (11) were obtained. Each couple of these parameters was considered to simulate \(ET_0\) of the one hundred groups of validation stations. Table 3 summarizes the key statistical indices of the two calibrated parameters. After the calibration, the values of \(\beta\) ranged between 25.8 up to 27.3 °C while the values of \(\delta\) varied between 0.390 and 0.397. The values of the standard deviation values were 0.2 for \(\beta\) and 0.003 for \(\delta\). These values have proven the stability of the calibrated parameters. The average value of calibrated \(\beta\) is less than its original value in Dorji model by approximately 22% while the value of calibrated \(\delta\) is greater to its original value by approximately 25%.

\[
ET_{0,\text{Hadria}} = 0.408 + 0.002 \times (T_{avg} + \betai) \times (T_{max} - T_{min})^{\delta} \times Ra_i
\]

Where \(\beta_i\) and \(\delta_i\) are the calibrated parameters \(\beta\) and \(\delta\) for the repetition number \(i (1 ≤ i ≤ 100)\). The one hundred \(ET_{0,\text{Hadria}}\) models were validated by applying them to the 1100 cases (11 validation stations per hundred variants).

The performance of the new models (Fig. 5 and Table 4) shows that the calibration process improved well \(ET_0\) simulation compared to \(ET_{0,PM}\). \(R^2\) values oscillate around 0.88 with a standard deviation of 0.01.
nRMSE values vary between 0.22 and 0.29 while PE values fluctuate around 11.88 with a standard deviation of 2.12. Obviously, instead of a hundred versions of the calibrated models, the average values of the two calibrated parameters $\beta$ and $\delta$ were adopted to suggest the best version which was, therefore, called $\text{ET}_0$-Hadria, and where the formula is given by:

$$\text{ET}_0\text{-Hadria} = 0.408 \times 0.002 \times (T_{avg} + 26.3) \times (T_{max} - T_{min}) ^ 0.397 \times R_i$$

(13)

$\text{ET}_0$-Hadria Model was applied to the 22 studied stations and the results were compared again to those obtained by $\text{ET}_0\text{-PM}$ (Fig. 6 and Table 5). The results confirm that the quality of the correlation between both estimates was improved; the slope increased by approximately 20%, and the intercept decreased by approximately 7%. The evaluation also showed that $\text{ET}_0$-Hadria improved the precision in most 68% of the stations (15 stations with clear lines shown in Table 5, see also Fig. 6c) against a decrease in precision in 32% of the stations (7 lines in bold). Moreover, PE was improved for 14 stations by 3–98% compared to the Dorji’s estimate.

Fig. 7 shows the spatial distribution of the stations for which the calibrated model improved the accuracy (green triangles) and the others stations for which the accuracy decreased (red triangles). The stations of the first group are mainly located in the flat area with elevation inferior to 500m, while the stations of the second group are located in the foothills of the High Atlas and Middle Atlas Mountains and in the arid regions of high Plateaus of Eastern Morocco. The calibration parameters for the Dorji’s estimate (mentioned above) explain the results of the second group.

Taking into account that the most extensive and important agricultural areas of Morocco are covered by the stations of the first group stations (Balaghi et al., 2007; Hadria et al., 2019), $\text{ET}_0$-Hadria gains ground largely to any other estimate in the flats areas and where the altitudes are lower than 500m under arid and semi-arid settings. In mountainous areas, and based on our analysis, Dorji’s estimate is more suitable.

4. Conclusions

Food and water crisis in many parts of the world, particularly arid and semi-arid, is not a recent puzzle to be solved, but the lockdowns warn of the need to ensure a minimum of self-sufficiency when trade or international aid stagnate. In this regard, scientific recommendations constantly kept warning of the immediate need to control the huge water losses by evapotranspiration, especially in the MENA and the Mediterranean regions, since it is one of the most efficient ways to ensure water and agricultural needs without jeopardizing the principles and standards of good governance. However, this was limited by the absence of an estimate unanimously approved for the climatic and geographic conditions of these areas. This has been corrected here, with the suggestion of an easy-to-use and accurate estimate to assess reference evapotranspiration.

Thus, abundant climatic data from 22 well-distributed weather stations in Morocco were used, chosen to be representative of the geomorphological diversity of the MENA region and the Mediterranean, the variability of their arid environments and the harshness of data availability.

Firstly, a comparison between reference evapotranspiration ($\text{ET}_0$), assessed via the standard FAO Penman-Monteith estimate ($\text{ET}_0\text{-PM}$), and climatic variables measured in all stations showed that $\text{ET}_0$ is strongly and positively correlated with solar radiation, average and maximum air temperatures, with a coefficient of determination ($R^2$) equal to 0.73, 0.64 and 0.62, respectively.

Then, five simple temperature-based $\text{ET}_0$ estimates (calibrated and validated under different climatic conditions worldwide) were compared to $\text{ET}_0\text{-PM}$. It was concluded that the Dorji’s estimate is the most accurate, so far, compared to the other four. Afterward, an advanced calibration of its two key parameters has been performed to improve its accuracy. After one hundred calibrations tests, a new fit-version was adopted to be the most suitable to assess $\text{ET}_0$ for arid and semi-arid areas and it was called, consequently, $\text{ET}_0$-Hadria. In comparison with $\text{ET}_0\text{-PM}$, the novel estimate shows an overall improvement in the quality and precision of reference evapotranspiration assessment, mainly in flat and under 500m altitude areas. It is supposed to, hopefully, help improving water management capacity in these areas, tackling priority order and guaranteeing the continuity of resource availability. However, the original version of Dorji model can be used in mountainous regions.

During the current unprecedented Covid-19 pandemic, decision-makers must take novel, reshaped and confident measures to ensure continuity of basic services while managing the superlative impact of the crisis. These measures need to be effective, creative, and meticulous to achieve its objectives, to move beyond powerlessness and to reduce speculative behaviors. New regulations, shapes and scales of coordination will be performed to mobilize, reallocate, and implement efficiently the resources to ensure health services, but also other critical areas such as security, education, energy, agriculture, and water. The resulting lessons must be well assimilated to prepare for the climate crisis which could be worse than the Covid-19 pandemic if the correct actions are not taken.

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CRedit authorship contribution statement

Rachid Hadria: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. Tarik Benabdellouhab: Investigation, Writing - review & editing. Hayat Lionboui: Writing - review & editing. Adil Salhi: Writing - review & editing.

Declaration of competing interest

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

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