Water Resources Management
https://doi.org/10.1007/s11269-022-03154-9

Sensitivity of the RDI and SPEI Drought Indices to Different Models for Estimating Evapotranspiration Potential in Semiarid Regions

Ruperto Ortiz-Gómez[1] · **Roberto S. Flowers-Cano**[2] · **Guillermo Medina-García**[3]

Received: 24 January 2022 / Accepted: 18 April 2022

Abstract
Drought research is of great importance for planning and management of water resources, due to the great impact that droughts have on society and ecosystems. In this study, the effect that using different models for calculating evapotranspiration has on the analysis of droughts in the semiarid region of North Central Mexico is investigated, using climatological information from 14 meteorological stations. Drought was analyzed using the Reconnaissance Drought Index (RDI) and the Standardized Precipitation Evapotranspiration Index (SPEI) at the scales of 3, 6 and 12 months. Eight evapotranspiration models were used: those of Thornthwaite, Hargreaves – Samani, Droogers – Allen, Allen, Dorji, Priestley – Taylor, Makkink and Irmak. According to three of the efficiency indices that were used – the root mean squared error (RMSE), the medium absolute error (MAE) and the concordance index – the Hargreaves – Samani model yields the best evapotranspiration results as compared to the Penman–Monteith model, whereas the models of Thornthwaite and Dorji are the least recommended for this purpose. The non-parametric Wilcoxon test, at a 5% significance level, leads to the conclusion that there are no statistically significant differences between the RDI and SPEI drought indices calculated using the Thornthwaite or the Hargreaves – Samani model. At the three scales of analysis, differences in the RDI index calculated using evapotranspiration estimated with the Thornthwaite or the Hargreaves – Samani model are minimal, but are slightly larger for the SPEI index. Drought events detected with the RDI and SPEI indices are more intense when the Thornthwaite model is used to calculate evapotranspiration instead of the Hargreaves – Samani model. These results may prove valuable in the analysis of droughts, especially in arid and semiarid regions.

Keywords Mexico · Drought · Reconnaissance drought index · Standardized precipitation evapotranspiration index · PET calculation methods · Rainfall

1 Introduction

Drought is one of the most complex, harmful and less understood climatic events, which causes millions of dollars in damages worldwide, and affects millions of people every year (Yagci et al. 2013; Halwatura et al. 2017). Drought affects the environment, agriculture,

✉ Ruperto Ortiz-Gómez
ortizgr@uaz.edu.mx

Extended author information available on the last page of the article

Published online: 02 May 2022

vegetation, human beings, wildlife, as well as local economies (Zarei et al. 2019), and is one of the greatest threats to human survival, which imposes serious adverse impacts on social, economic and environmental sustainability. It is expected that the frequency and severity of droughts will increase in the future due to climate change (Mishra and Singh 2009; Dai 2011).

A drought can be defined as a recurrent natural climatic event caused by less than normal precipitation as compared with the long-term average, which extends over a long period of time (Hisdal and Tallaksen 2003; Dai 2011). Drought must be considered as a three – dimensional event, characterized by its severity or intensity, its duration, and its affected area (Tsakiris and Vangelis 2005; Vangelis et al. 2013). Droughts are classified in four main types: meteorological, agricultural, hydrological and socioeconomic (Heim 2002; Bayissa et al. 2018). Timely monitoring of meteorological drought is essential for early warning and risk management of water resources and agricultural production.

To identify drought and monitor its development, many different indices have been proposed and applied (Yuan and Quiring 2014; Zhang et al. 2015), which are used to quantify and compare the severity, duration and extension of droughts in regions with varied climatic and hydrological regimes (Vangelis et al. 2013; Zhang et al. 2016). Such indices are based on indicator variables such as precipitation, soil moisture, runoff and evapotranspiration (Ortiz-Gómez et al. 2018; Yue et al. 2018). Among the most prominent indices according to their worldwide use figure Palmer´s Drought Severity Index (PDSI; Palmer 1965), the Standardized Precipitation Index (SPI; McKee et al. 1993), the Reconnaissance Drought Index (RDI; Tsakiris and Vangelis 2005) and the Standardized Evapotranspiration Index (SPEI; Vicente-Serrano et al. 2010). The SPI is probably the index that is most used around the world, due to its simplicity and to the fact that it uses only precipitation data. The SPI has shown its usefulness in drought monitoring and early warning, but it exhibits deficiencies in that it is unable to identify drought conditions caused not by lack of precipitation, but by an above normal demand of atmospheric evaporation (Mohammed and Scholz 2017a). The main limitation of the SPI is that it is completely based on precipitation data, and it ignores other variables such as temperature, which affect the demand of surface water (McEvoy et al. 2012).

Evapotranspiration is an essential parameter of the drought phenomenon, especially in arid and semiarid regions. Consideration of this parameter in the evaluation of droughts by means of selecting an appropriate index increases the validity of results (Khanmohammadi et al. 2018). In an effort to improve the SPI, the RDI and SPEI indexes were developed, which incorporate the potential evapotranspiration (PET) as an estimation of the demand of atmospheric water. The RDI is calculated as the ratio of precipitation to potential evapotranspiration (Tsakiris and Vangelis 2005). As an improvement to the SPI, the RDI calculates the aggregate deficit between the atmosphere´s evaporative demand and precipitation, and is a multiscalar index. The RDI has been applied in numerous places worldwide, particularly in arid and semiarid regions, and is characterized by its high sensitivity and resistance, and by its low data requirement (Tigkas et al. 2012; Mohammed and Scholz 2017b). On the other hand, the SPEI uses precipitation – evapotranspiration differences as input data, instead of only precipitation data. The SPEI combines sensitivity to changes in water demand (caused by temperature fluctuations and trends) and the multitemporal nature of the SPI (Vicente-Serrano et al. 2010). The SPEI may be a useful drought indicator, since evapotranspiration is the main form of water loss in dry regions with high temperatures (Tirivarombo et al. 2018).

To determine atmospheric water demand in the study of drought using the RDI and the SPEI, the use of Thornthwaite's model (Thornthwaite 1948) was initially proposed, since it only requires temperature data and the latitude of the study site. The wind velocity, surface humidity and solar radiation, which also affect evapotranspiration are not considered in its estimation. Van der Schrier et al. (2011) and Sheffield et al. (2012), among others, indicate that Thornthwaite´s model overestimates evapotranspiration in humid equatorial and tropical regions, and underestimates evapotranspiration in arid and semiarid regions. The use of different evapotranspiration models to estimate drought indices has been studied by different researchers (e.g., Vangelis et al. 2013; Vicente-Serrano et al. 2015; Zhang et al. 2016). However, their results disagree on the magnitude of impact which the method used for estimating evapotranspiration has on drought indices. Therefore, further research on the impact of evapotranspiration estimation methods on drought analysis is needed, especially in arid and semiarid regions. Namely, determining the sensitivity of drought indices to the evapotranspiration estimation method is important in these regions.

The main objectives of this work are: (1) to determine, among eight analyzed models, which is the best for estimating evapotranspiration using minimal climatological information in the semiarid region of North Central Mexico; (2) to evaluate the potential impact (examine the sensitivity) of some of the analyzed evapotranspiration models in the estimation of drought characteristics using the RDI and SPEI indices, at scales of 3, 6 and 12 months. The novelty of this work lies in the use of evapotranspiration data obtained directly by means of the Penman – Monteith model, which is unusual in Mexico due to lack of information. With these data, it was possible to select an empirical PET estimation method, and to study its impact on the analysis of droughts using the RDI and SPEI indices.

2 Materials and Methods

2.1 Characteristics of the Study Area

Mexico is located at the same latitude as the Sahara and Arabian deserts, and two thirds of its territory are considered arid or semiarid, with annual precipitations below 500 mm (Comisión Nacional del Agua (CONAGUA) 2018). The state of Zacatecas, which is the study region of this research, has a surface area of 75 284 km^2, and is located in Central Mexico, between 25° 07′ 31″ and 21° 02′ 31″ North latitude, and between 100° 44′ 32″ and 104° 21′ 13″ West longitude (Instituto Nacional de Estadística y Geografía (INEGI) 2015), and its elevation varies between 788 and 3162 m above mean sea level, with an average value of 2054 m. Zacatecas exhibits mostly dry and semidry weather (73%), and temperate sub humid weather (17%), with a mean annual precipitation of around 510 mm, which ranges from 300 mm in the North, to 860 mm in the South; 75% of rainfall happens in summer (June to September).

2.2 Climatological Information

To determine the best models for estimating evapotranspiration, series of daily climatological data of maximum and minimum air temperature and evapotranspiration from five automatic stations in Zacatecas were used, which belong to the National Network of Automated Agrometeorological Stations of the National Institute of Forestry, Agriculture and Livestock Research (INIFAP, as per its Spanish acronym). These series cover the 2009–2019 period, and have an average percentage of missing data of 0.21%. Daily precipitation and maximum and minimum temperature data from 14 meteorological stations in and around Zacatecas, from the CLICOM (CONAGUA 2020) database, were also used to evaluate the RDI and SPEI drought indices. These series span from 1961 to 2018, and have an average percentage of missing data of 10.1%. In total, 19 climatological stations were used, whose geographical descriptors, as well as their mean annual precipitation (P_m) and temperature (T_m) are shown in Table 1, while their locations are shown in Fig. 1.

2.3 Methodology

Nine evapotranspiration models and two drought indices were used in this research. Of the nine evapotranspiration models, the Penman–Monteith model was used as a reference, against which the other eight simpler models were compared. The comparison of the PET models and their impact on drought analysis was done in six stages: 1) selection and quality control of the climatological information; 2) calculation of the PET using information from INIFAP; 3) determination of the best model for PET estimation by comparison to the Penman–Monteith model; 4) calculation of the RDI and SPEI indices at the timescales of 3, 6 and 12 months, considering the PET estimated with the models that exhibit the best and worst efficiency indices in relation to the Penman–Monteith model; 5) sensitivity analysis of the drought indices considering the PET models used in stage (4); and (6) evaluation of the impact of PET on drought intensity according to the RDI and SPEI indices.

2.3.1 Selection of Climatological Information

Selection of INIFAP stations to determine the best PET estimation model was done following two criteria: 1) record length should be of at least 10 years, and 2) selected stations should be the closest possible (not more than 30 km) to the meteorological stations from CONAGUA´s CLICOM (CLImate COMputing project) database. The selection of the climatological information from the CLICOM database used to calculate the drought indices was based on four criteria: 1) meteorological stations should be active; 2) record length should be of at least 45 years; 3) the percentage of missing data should be less or equal to 15%; and 4) stations should be distributed throughout the entire study area.

2.3.2 PET Calculation Models

Different models have been developed to calculate PET, which have been grouped into various categories: based on temperature, based on radiation, based on mass transfer, combined, among others (Gocic and Trajkovic 2010). Temperature based models only require temperature input to calculate PET, which include the models of Thornthwaite (Thornthwaite 1948), Blaney Criddle (Blaney and Criddle 1950), Hargreaves-Samani (Hargreaves and Samani 1985), etc. Radiation based models are based on an energy balance, and include the models of Makkink (Makkink 1957), Jensen-Haise (Jensen and Haise 1963), Priestley and Taylor (Priestley and Taylor 1972), Irmak (Irmak et al.

Table 1 Geographic location and information from the meteorological stations used in the study

Station	Name	Source	Latitude (°N)	Longitude (°W)	Altitude (masl)	Period	Pm (mm)	Tm (ºC)
15933	Campo Uno	INIFAP	24.1189	103.3888	2140	2009–2019	455.2	16.3
18779	Agua Nueva	INIFAP	23.7823	102.1600	1913	2009–2019	392.6	18.1
18879	CBTA Tepechitlán	INIFAP	21.6386	103.3304	1765	2009–2019	681.1	18.9
18851	CEZAC*	INIFAP	22.9087	102.6594	2197	2009–2019	437.0	16.0
18663	Loreto	INIFAP	22.2788	102.0013	2028	2009–2019	436.1	16.4
32036	Mazapil	CLICOM	24.6406	101.5558	2274	1961–2018	485.2	16.0
32028	Juan Aldama	CLICOM	24.2817	103.3978	1999	1961–2018	449.2	17.9
32001	Agua Nueva	CLICOM	23.7833	102.1603	1946	1961–2018	365.9	17.7
32006	El Cazadero	CLICOM	23.6931	103.0936	1862	1961–2018	404.8	16.8
32018	El Sauz	CLICOM	23.2817	103.1089	2096	1961–2018	429.6	16.0
32003	Calera	CLICOM	22.9086	102.6597	2097	1961–2018	439.9	15.6
32030	La Florida	CLICOM	22.6861	103.6025	1870	1961–2018	606.7	16.5
32024	Guadalupe Victoria	CLICOM	22.3958	101.8314	2132	1971–2018	390.9	16.4
32032	La Villita	CLICOM	21.6047	103.3378	1786	1961–2018	778.1	20.8
32039	Nochistlán (DGE)	CLICOM	21.3575	102.8456	1853	1961–2018	716.0	18.5
10047	Narciso Mendoza	CLICOM	23.9422	103.9600	2063	1961–2018	505.5	17.2
24094	Vanegas	CLICOM	23.8853	100.9514	1738	1961–2018	277.4	17.6
1020	Presa La Codorniz	CLICOM	21.9967	102.6742	1850	1961–2018	617.7	18.4
1032	Las Fraguas	CLICOM	22.0392	101.8925	2086	1971–2018	466.1	16.9

*Campo Experimental Zacatecas

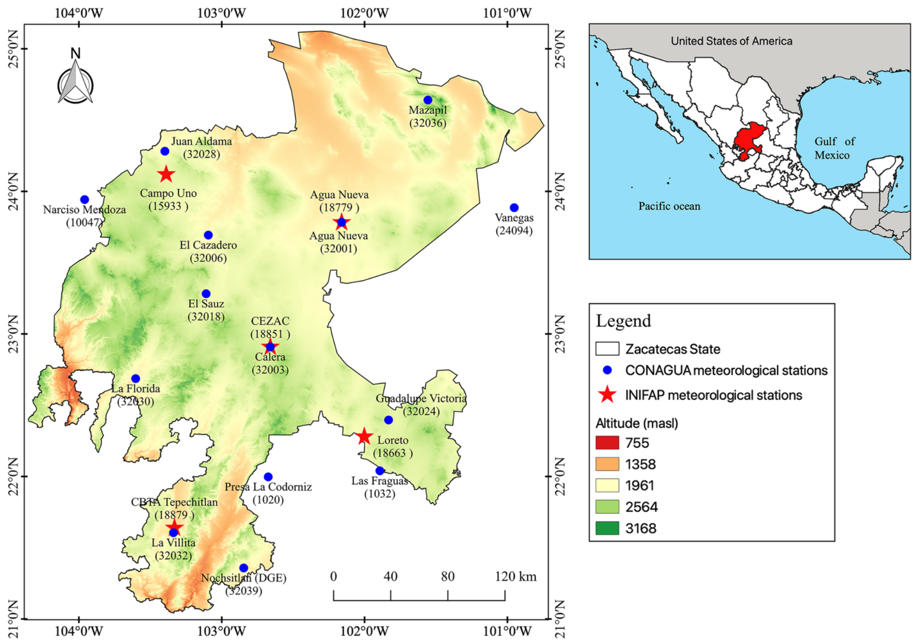


Fig. 1 Location of selected meteorological stations

2003), etc. Meanwhile, mass transfer models are based on Dalton´s evapotranspiration law, and take into account meteorological factors such as wind, temperature, humidity, among others. This category includes the models of Rohwer (Rohwer 1931), Ivanov (Romanenko 1961), etc. Combined models consider aerodynamic influence and require a great number of parameters and a more complicated calculation process. The models of Penman (Penman 1948) and Penman – Monteith (Allen et al. 1998) fall into this category.

In this research, five temperature-based and three radiation-based PET models were evaluated to determine which gives results closest to those obtained with the Penman–Monteith PET model (reference model).

Combined Model The Penman–Monteith model was used as a reference model for PET calculation.

Penman–Monteith Model (Allen et al. 1998)

$$PET = \frac{0.408\Delta\left(R_n - G\right) + \gamma\frac{900}{T_a+273}u_2\left(e_s - e_a\right)}{\Delta + \gamma\left(1 + 0.34u_2\right)} \tag{1}$$

where: PET is reference or potential evapotranspiration (mm day^{-1}); R_n is net radiation (MJ m^{-2} day^{-1}); G is soil heat flux (MJ m^{-2} day^{-1}); γ is the psychrometric constant (kPa ºC^{-1}); T_a is mean daily air temperature (ºC); u_2 is wind speed (m s^{-1}) at 2 m above the ground; e_s is saturated vapor pressure (kPa); e_a is current vapor pressure (kPa); Δ is the slope of the pressure curve (kPa°C^{-1}) at air temperature. For PET calculation at a daily scale, G may be considered negligible ($G = 0$, Allen et al. 1998).

Temperature-Based PET Models The following five temperature-based models were used in this research:

Thornthwaite model (Thornthwaite 1948)

$$PET = 16\left(10\frac{T_a}{I}\right)^a \tag{2}$$

where: I is annual heat index; and a is given by a third-order polynomial that depends on I.

Hargreaves – Samani model (Hargreaves and Samani 1985)

$$PET = 0.408 \times 0.0023 \times \left(T_a + 17.8\right) \times \left(T_{max} - T_{min}\right)^{0.5} \times R_a \tag{3}$$

where: T_{max} y T_{min} are, respectively, maximum and minimum temperature (°C); and R_a is extraterrestrial radiation (MJ m^{-2} day^{-1}).

Droogers – Allen model (Droogers and Allen 2002)

$$PET = 0.408 \times 0.0025 \times \left(T_a + 16.8\right) \times \left(T_{max} - T_{min}\right)^{0.5} \times R_a \tag{4}$$

Allen model (Allen 1993)

$$PET = 0.408 \times 0.0030 \times \left(T_a + 20\right) \times \left(T_{max} - T_{min}\right)^{0.4} \times R_a \tag{5}$$

Dorji model (Dorji et al. 2016)

$$PET = 0.408 \times 0.0020 \times \left(T_a + 33.9\right) \times \left(T_{max} - T_{min}\right)^{0.296} \times R_a \tag{6}$$

Radiation-Based PET Models The following three radiation-based models were used in this research:

Priestley – Taylor model (Priestley and Taylor 1972)

$$PET = 1.26\frac{\Delta}{\Delta + \gamma}\frac{R_n - G}{\lambda} \tag{7}$$

Makkink model (Makkink 1957)

$$PET = 0.61\frac{\Delta}{\Delta + \gamma}\frac{R_s}{\lambda} - 0.12 \tag{8}$$

Irmak model (Irmak et al. 2003)

$$PET = -0.611 + 0.149R_s + 0.079T_a \tag{9}$$

Evapotranspiration models were designated as follows: Penman–Monteith model (PM), Thornthwaite model (TW), Hargreaves – Samani model (HG), Droogers – Allen model (DOO), Allen model (ALL), Dorji model (DRJ), Priestley – Taylor model (PT), Makkink model (MKK) and Irmak model (IMK).

2.3.3 Drought Indices

Drought Reconnaissance Index (RDI) The RDI allows the assessment of the severity of a drought, and can be calculated at different time scales (monthly, seasonal or annual). The RDI is expressed in three forms: RDI initial value (α_k), normalized RDI (RDIn) and standardized RDI (RDIst). In this research, the RDI was calculated fitting the Gamma distribution to the α_k values. Detailed descriptions of the RDI calculation can be found in Tsakiris et al. (2007), Vangelis et al. (2013), Ortiz-Gómez et al. (2018), among others. Drought severity may be classified into four classes: light, moderate, severe and extreme. The respective limits of RDI are −0.5 to −0.99, −1.0 to −1.49, −1.5 to −1.99, and ≤ −2.0, respectively.

Standardized Precipitation-Evapotranspiration Index (SPEI) The SPEI is based on a monthly climatic water balance (precipitation minus potential evapotranspiration – called *D* series), which is calculated at different time scales. Its calculation follows a similar approach to the one followed for the calculation of the RDI, but using a three-parameter Log-logistic distribution instead of a two-parameter Gamma distribution. The RDI drought classification may be used to assess the SPEI.

Detailed descriptions of the SPEI calculation can be found in Vicente-Serrano et al. (2010), Ortiz-Gómez et al. (2018), Tirivarombo et al. (2018), among others.

2.3.4 Evaluation Criteria for the PET, RDI and SPEI

Four efficiency indices and one statistic test were applied in this research: 1) the root mean squared error (*RMSE*); 2) the mean absolute error (*MAE*); 3) the concordance index (*d*); 4) the determination coefficient (R^2); and 5) the Wilcoxon test for comparison of means. The first three of these criteria were used in the comparison of the different evapotranspiration models against the Penman – Monteith model (reference model), whereas the last two criteria were used to evaluate the effect of the different PET calculation models on the RDI and SPEI indices.

The four efficiency indices are defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_i - O_i\right)^2} \tag{10}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - O_i\right| \tag{11}$$

$$d = 1 - \left[\frac{\sum_{i=1}^{N}\left(P_i - O_i\right)^2}{\sum_{i=1}^{N}\left(\left|P_i - \overline{O}\right| + \left|O_i - \overline{O}\right|\right)^2}\right] \tag{12}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(y_{e,i}-\overline{y}_e\right)\left(y_{o,i}-\overline{y}_o\right)\right]^2}{\sum_{i=1}^{n}\left(y_{e,i}-\overline{y}_e\right)^2\sum_{i=1}^{n}\left(y_{o,i}-\overline{y}_o\right)^2} \tag{13}$$

where: N represents the total number of daily or monthly PET observations; P_i are daily or monthly PET values estimated using the analyzed PET models, in mm/day and mm/month, respectively; O_i are daily or monthly PET values calculated using the PM model (reference model), in mm/day and mm/month, respectively; $\overline{O}$ is the mean of daily or monthly PET values calculated using the PM model, in mm/day and mm/month, respectively; n represents (in this case), the total number of data values in the RDI and SPEI drought index series for the three scales of analysis; $y_{e,i}$ are the RDI and SPEI values estimated using PET values obtained with the best fitting PET model; $y_{o,i}$ are the RDI and SPEI values calculated from PET values obtained with the TW model; $\overline{y}_e$ is the mean value of the RDI or the SPEI calculated from PET values obtained with the best fitting model; and $\overline{y}_o$ is the mean value of the RDI or the SPEI calculated from PET data obtained with the TW model.

The *RMSE* and *MAE* efficiency indices vary from zero to infinity; however, the smaller its values, the better the fit (optimum value = 0), and have the same units as the analyzed variables.

The d and R^2 indices vary from 0 to 1, and the highest values indicate the best fit (optimum value = 1).

3 Results and Discussion

3.1 Daily Analysis of Evapotranspiration Models

Using the data from the five INIFAP meteorological stations, daily PET was estimated by applying seven of the temperature-based and radiation-based evapotranspiration models described in Sect. 2.3.2 (the TW was not used at a daily scale). The results that were obtained were compared with the PET estimated using the standard Penman – Monteith (PM) model. Efficiency indices *RMSE*, *MAE* and d, were calculated for each of the PET models which were evaluated against the PM model.

The results of the efficiency indices obtained at a daily scale are shown in Table 2. The *RMSE* presented a variation from 0.76 to 1.93 mm/day at Loreto (HG) and CEZAC (DRJ) stations, respectively, with a mean value of 1.26 mm/day across all five stations. Meanwhile, the MAE index had values ranging from 0.59 to 1.79 mm/day, which happened at Loreto (HG) and Agua Nueva (DRJ) stations, respectively, with a mean value of 1.07 mm/day. Finally, the concordance index d exhibited a variation ranging from 0.91 (Loreto, HG and DOO) to 0.62 (CEZAC, DRJ), with a mean value of 0.80.

In all five analyzed stations, the PT model overestimated PET. The greatest overestimation happened at CBTA Tepechitlán station, mainly from May to August. On the other hand, the DRJ model always underestimated PET in all five meteorological stations. It is worth noting that the DRJ model was developed for the monsoon region of Southern Asia (Dorji et al. 2016).

At stations Campo Uno and CEZAC, in Northwestern and Central Zacatecas, all evaluated models except PT underestimate PET values in comparison to those obtained with PM. At stations Agua Nueva, CBTA Tepechitlán and Loreto, the HG, ALL and DOO

Table 2 Efficiency indices of the daily PET estimation models respect to the Penman Monteith model

Models	Agua Nueva			Campo Uno			CBTA Tepechitlán			CEZAC			Loreto		
	RMSE	MAE	d	RMSE	MAE	d	RMSE	MAE	d	RMSE	MAE	d	RMSE	MAE	d
Hargreaves – Samani (HG)	0.97	0.97	0.88	0.94	0.72	0.88	1.02	0.82	0.85	0.98	0.78	0.88	0.76	0.59	0.91
Allen (ALL)	1.02	1.02	0.87	0.98	0.76	0.87	1.17	0.96	0.81	0.96	0.76	0.88	0.82	0.64	0.89
Droogers – Allen (DOO)	1.01	1.01	0.88	0.93	0.73	0.89	1.25	1.06	0.80	0.90	0.70	0.90	0.80	0.63	0.91
Dorji (DRJ)	1.79	1.79	0.64	1.78	1.49	0.63	1.13	0.95	0.73	1.93	1.66	0.62	1.61	1.39	0.65
Priestley – Taylor (PT)	1.59	1.59	0.80	1.66	1.30	0.78	1.88	1.51	0.70	1.37	1.10	0.85	1.50	1.20	0.79
Makkink (MKK)	1.61	1.61	0.71	1.56	1.27	0.71	1.05	0.83	0.81	1.59	1.32	0.73	1.40	1.18	0.74
Irmak (IMK)	1.34	1.34	0.76	1.36	1.06	0.75	0.83	0.62	0.85	1.39	1.10	0.76	1.17	0.94	0.78

RMSE (mm/day) is the root mean squared error of each adopted PET model respect to the Penman Monteith model, *MAE* (mm/day) is the mean absolute error of each adopted PET model respect to the Penman Monteith model, *d* is the concordance index of each adopted model respect to the Penman Monteith model models slightly overestimate PET in comparison to PM, from May to August, whereas the DRJ, MKK and IMK models always underestimate PET. The results of the three efficiency indices lead to the conclusion that, at a daily level, among the seven evaluated PET models, the HG model yields the best results for the state of Zacatecas using the minimum amount of weather information. The DOO model exhibits slightly lower efficiency indices to those of the HG model. The efficiency indices of the HG model range from 0.76 to 1.02 mm/day for the *RMSE*, from 0.59 to 0.97 mm/day for the *MAE*, and from 0.91 to 0.85 for the concordance index *d*. On the other hand, the DRJ model exhibits the worst efficiency indices in four of the five stations; this model gives the greatest overestimation of PET values in comparison to those obtained with the PM model. CBTA Tepechtitlán station is located at a lower altitude, and exhibits greater mean annual precipitation and temperature than the other stations (Table 1). These conditions affect PET estimation, as reflected by the efficiency indices obtained in the comparison between estimated PET and reference PET obtained using the PM model (Table 2).

In general, results from this research concerning PET estimation agree with those of López-Urrea et al. (2006) and Tabari (2010), among others, in that the Hargreaves – Samani (HG) model yields good results for arid and semiarid regions, although it generally underestimates PET (Azhar and Perera 2010). On the other hand, the PT and MKK models behaved poorly at estimating PET, in agreement with results obtained by Tabari (2010) for semiarid climates.

3.2 Monthly and Annual Analysis of the Evapotranspiration Models

For each of the five INIFAP stations analyzed in this research, PET at monthly scale was obtained with daily PET values estimated using the seven models applied at the daily scale. Additionally, PET at the monthly level was estimated using the TW model and reference values of monthly PET were calculated with the PM model.

Table 3 shows the efficiency indices for the monthly values of PET. Efficiency indices at a monthly level show an improvement with respect to the daily level, as is seen in the values of the concordance index, since PET variability is reduced at a monthly scale. Results show that the *RMSE* ranges from 13.26 to 81.41 mm/month, at Loreto and CEZAC stations, respectively. The *MAE* efficiency index varies between 10.40 and 76.91 mm/month, at Loreto and CEZAC stations, respectively, and the concordance index *d* varies from 0.96 to 0.48, both values from Loreto station, but for the HG and TW models, respectively. Figure 2 shows, representatively, monthly PET estimated using the eight adopted models and the reference model PM. It is observed that, excepting the PT model, all other models underestimate PET in comparison to the PM model. The TW model exhibits the worse fit with respect to the PM model, which can also be observed in Table 3, where the TW has the worst efficiency values of all the evaluated models. In general, the results of the efficiency indices for monthly PET confirm what was observed at a daily level, that the Hargreaves – Samani (HG) is the model which produces the best estimations for the study zone, followed by the DOO model, whereas the TW model is the least recommended for this purpose, followed by the DRJ model.

PET calculated with the PM model at CEZAC station had an average value of 1681 mm/year, whereas with the TW model, which was the model originally used in the development of the RDI and SPEI drought indices, the average value was 758 mm/year, that is, 55% less than with the PM model. In turn, with the PT model, which overestimated PET with respect to PM, an average PET of 1969 mm/year was obtained, that is, 17% more than with

Table 3 Efficiency indices of the monthly PET estimation models respect to the Penman Monteith model

Models	Agua Nueva			Campo Uno			CBTA Tepechitlán			CEZAC			Loreto		
	RMSE	MAE	d	RMSE	MAE	d	RMSE	MAE	d	RMSE	MAE	d	RMSE	MAE	d
Thornthwaite (TW)	77.14	72.01	0.51	76.53	71.31	0.49	58.96	54.56	0.54	81.41	76.91	0.48	75.82	72.12	0.48
Hargreaves – Samani (HG)	21.93	18.02	0.91	17.94	14.95	0.93	25.65	22.71	0.86	19.53	14.91	0.92	13.26	10.40	0.96
Allen (ALL)	23.35	19.25	0.90	19.25	16.34	0.93	30.79	27.80	0.81	17.87	14.21	0.94	15.74	13.03	0.94
Droogers – Allen (DOO)	23.78	19.53	0.90	17.97	15.37	0.94	34.07	31.19	0.79	16.13	12.75	0.95	15.56	12.89	0.95
Dorji (DRJ)	48.98	43.54	0.64	47.35	42.13	0.64	27.71	24.03	0.77	52.46	47.54	0.62	43.46	40.00	0.65
Priestley – Taylor (PT)	41.70	33.73	0.80	43.11	34.09	0.78	52.49	44.30	0.67	36.89	29.23	0.84	40.17	32.92	0.79
Makkink (MKK)	43.84	38.35	0.68	40.79	35.21	0.70	25.27	21.47	0.81	44.19	39.33	0.68	38.00	34.41	0.70
Irmak (IMK)	34.84	27.99	0.74	33.79	26.52	0.75	17.02	11.32	0.90	37.19	30.79	0.73	29.93	24.83	0.77

RMSE (mm/month), *MAE* (mm/month)

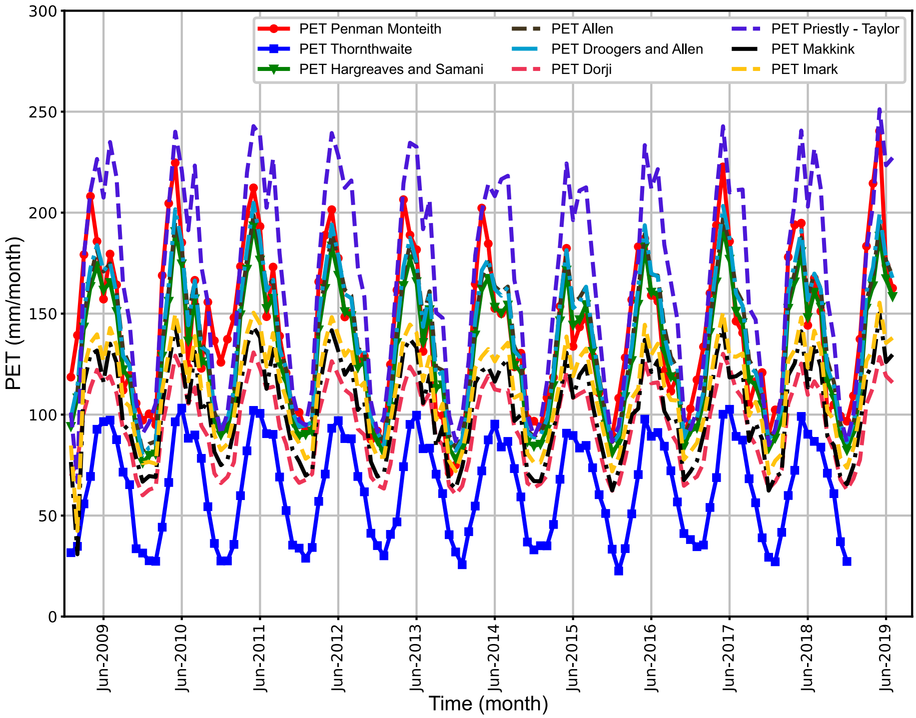


Fig. 2 Monthly evapotranspiration estimated at CEZAC station, Zacatecas, Mexico

the PM model. The HG and DOO models, which produce the best PET estimations with respect to PM, give average values of 1548 and 1634 mm/year, that is 8% less and 2.8% less, respectively.

According to the evaluation of the PET estimation models, and to meet the objective of this research, which is determining the importance of PET in the estimation of the RDI and SPEI drought indices, the models of Hargreaves – Samani (HG) and Thornthwaite (TW) were selected as the best and worst PET estimation models, respectively, with respect to the PM model.

3.3 Long Term Calculation of PET

The first step for calculating the RDI and SPEI drought indices consisted in estimating long term monthly PET, using information from the 14 selected CONAGUA meteorological stations. According to results from previous sections, PET estimated with the HG model was greater than that estimated with the TW model. For the 14 meteorological stations which were analyzed in this second stage, annual PET calculated with the TW model had a variation from 748 to 1014 mm, with a mean value of 819 mm, whereas with the HG model it varied from 1544 to 1856 mm, with a mean value of 1693 mm. The HG model gives, on average, values of annual PET 874 mm greater than those obtained with the TW model. Inter annual PET variation estimated with the HG model is greater than that estimated with

Fig. 3 RDI and SPEI drought indices in Northern (Juan Aldama station) and Southern (Nochistlán station) Zacatecas, Mexico

the TW model, which exhibits a more homogeneous behavior over time. That is to say, the HG model is more sensitive to variations in temperature values.

3.4 Calculation of the RDI and SPEI Indices

Once the PET values had been estimated using the TW and HG models, the next step was to calculate the RDI (α_k) and SPEI drought indices in the three selected scales for the 14 analyzed stations.

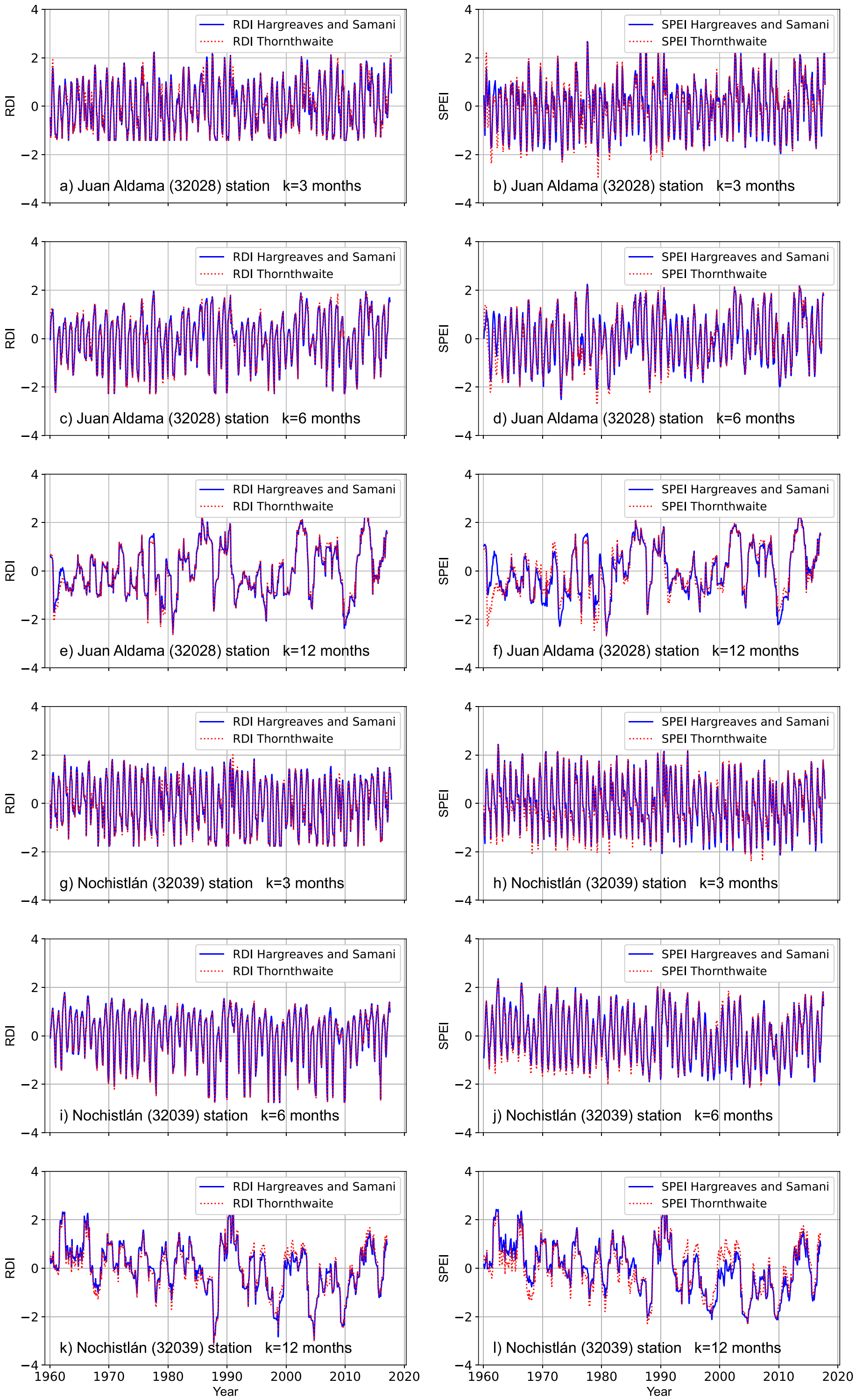
Figure 3 shows some of the results of the RDI and SPEI indices in graphic form, for Northern and Southern Zacatecas, at short, medium and long terms (three, six and twelve months). It is observed in the figure that differences in the RDI indices calculated using PET estimated with the TW or HG models are minimal. The slight differences that appear in some of the years cannot be considered significant, since they do not affect the severity of droughts. Only in few cases does a drought change its class, particularly at the 12-month scale. In the case of the SPEI, differences in the index calculated using PET obtained by the TW and the HG models are slightly greater than those of the RDI, and the greatest differences are observed at the 12-month scale. However, they do not seem to be significant either.

These results seem to support the assumption by Vicente-Serrano et al. (2010), that the PET estimation method is not critical in the calculation of drought indices, since its purpose is to provide a relative temporal estimation of evapotranspiration. Since in practice, the RDI is less sensitive to evapotranspiration than the SPEI (Vicente-Serrano et al. 2015), the effect of the PET estimation method is less for the RDI than for the SPEI.

The short-term evolution of the RDI and SPEI series exhibited a high temporal frequency of dry and wet periods. In the medium and long terms, dry and wet periods had a lower temporal frequency and a greater duration. Dry and wet periods are more clearly defined at a twelve-month scale. In the three scales of analysis, drought events detected with the RDI and the SPEI are more intense when the TW model is used to calculate PET instead of the HG model. However, the difference between intensities calculated using the two PET models is smaller for the RDI. The use of the TW model has a greater impact on the calculation of the SPEI, particularly at the scales of three and six months. When the HG model is used, the difference in the intensities of drought events calculated with the RDI and the SPEI are practically non-existent at the three-month time scale. Nevertheless, at the scales of six and twelve months, the RDI presents more intense drought events than the SPEI, which are of a different category in many cases.

3.5 Sensitivity of the RDI and SPEI to PET Estimation Models

When comparing the RDI drought index obtained using PET estimated with the TW or the HG model, and the drought index SPEI obtained using the same PET estimation models, it is observed that the determination coefficient R^2 is greater for the RDI than for the SPEI in the 14 meteorological stations and the three time scales which were analyzed (Fig. 4). At the three-month scale, R^2 varies from 0.94 to 0.99 for the RDI, with an average value of 0.97, and from 0.80 to 0.97 for the SPEI, with an average value of 0.93. At the six-month scale, R^2 ranges from 0.94 to 0.99 for the RDI, with an average value of 0.98, and from


RDI Hargreaves and Samani
RDI Thornthwaite
SPEI Hargreaves and Samani
SPEI Thornthwaite
a) Juan Aldama (32028) station k=3 months
b) Juan Aldama (32028) station k=3 months
c) Juan Aldama (32028) station k=6 months
d) Juan Aldama (32028) station k=6 months
e) Juan Aldama (32028) station k=12 months
f) Juan Aldama (32028) station k=12 months
g) Nochistlán (32039) station k=3 months
h) Nochistlán (32039) station k=3 months
i) Nochistlán (32039) station k=6 months
j) Nochistlán (32039) station k=6 months
k) Nochistlán (32039) station k=12 months
l) Nochistlán (32039) station k=12 months
RDI
SPEI
4
2
0
−2
−4
1960
1970
1980
1990
2000
2010
2020
Year

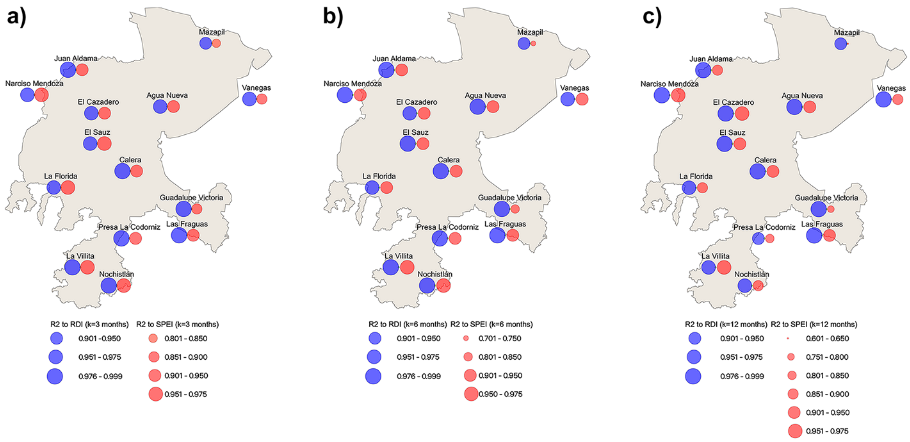


Fig. 4 Determination coefficient of the RDI and SPEI drought indices using PET estimated with the TW or the HG model in the three time scales

0.74 to 0.96 for the SPEI, with an average value of 0.93. Finally, at the twelve-month scale, R^2 varies from 0.94 to 1.00 for the RDI, with an average value of 0.98, and from 0.63 to 0.96 for the SPEI, with an average value of 0.91. From these results it is observed that there is no significant difference in the calculation of the RDI and SPEI indices whether the TW or the HG model is used, regarding the analysis of droughts in Central Mexico.

In 86% of the analyzed meteorological stations, R^2 increases for the RDI as the scale of analysis increases, whereas for the SPEI, this only happens in 57% of the analyzed stations. In order to statistically evaluate the difference in means between the RDI and SPEI values calculated using PET estimated with the TW or the HG model, the Wilcoxon test was used at a 5% significance level. Results indicate that, in 100% of the 84 evaluated drought index series, there are no statistically significant differences between the RDI and SPEI indices calculated using the TW or the HG model.

Regarding the SPEI, results obtained in this research agree with those obtained by Vicente-Serrano et al. (2015) and Zhang et al. (2019), in that the SPEI is sensitive to the PET model used in its calculation. However, results from this research are not statistically significant. On the other hand, results concerning the behavior of the RDI (α_k), are similar to those found for the RDIst, by Vangelis et al. (2013) in Greece at the same scales of analysis, by Zarei and Mahmoudi (2017) in Iran at a one month scale, and by Mohammed and Scholz (2017a) in different parts of the world at a twelve month scale. These authors found that the influence of using different PET models was not significant in the calculation of the RDI. However, results from this research differ from those obtained for the RDI (α_k) by Mohammed and Scholz (2017a) at a twelve month scale, since in this case, they found that the influence of the PET models was statistically significant (p_value < 0.05).

In practice, the RDI is more sensitive to precipitation than to evapotranspiration, as suggested by the strong correlation shown in some studies between the RDI and the SPI (Tsakiris et al. 2007; Zarch et al. 2011; Ortiz-Gómez et al. 2018). Theoretically, the SPEI is equally sensitive to precipitation and evapotranspiration, and in practice is generally more sensitive to evapotranspiration than the RDI (Vicente-Serrano et al. 2015). When applied to the state of Zacatecas, whose climate is dry but not particularly warm, the RDI would detect more intense droughts, because of the low precipitation, whereas the SPEI would detect less intense droughts, because even though the precipitation is low, evapotranspiration is not particularly high. The different sensitivities of the RDI and SPEI indices to precipitation and evapotranspiration is probably a consequence of how these indices are defined. The RDI is based on the quotient between precipitation and evapotranspiration, and is sensitive to variations in the standard deviations, but not to variations in the mean values of these variables. Thus, since precipitation usually has greater standard deviations than evapotranspiration, the RDI is in practice more sensitive to precipitation than to evapotranspiration. On the other hand, the SPEI is based on the difference between precipitation and evapotranspiration, and is sensitive to variations in both the means and the standard deviations of these variables. Thus, in practice, the SPEI is sensitive to evapotranspiration in many different scenarios, and is generally more sensitive to this variable than the RDI (Vicente-Serrano et al. 2015).

The results on the RDI found here strengthen the idea that the RDI is a robust index for evaluating drought severity, which does not depend on the model used to calculate PET, particularly in arid and semiarid regions, at different scales of analysis.

These results may be of great relevance for drought analysis in Mexico, since two thirds of its territory are considered arid or semiarid, which are inhabited by approximately 40% of its population, and generate 79% of its gross domestic product.

3.6 Influence of PET in Drought Intensity

In order to determine the years with the most important drought events during the period of analysis, the 15 events with the greatest intensity were analyzed. These events were detected using the RDI as well as the SPEI, which were calculated using both the HG and the TW models to estimate PET. At the three-month scale, the years with several greater intensity events were 2011 and 1999 according to the RDI, and the years 2012, 2011 and 1998 according to the SPEI. At the six-month scale, the years with several greater intensity events were 2011, 2000, 1999, 1991 and 1989 according to the RDI, and the years 2011, 1998, 1989 and 1982 according to the SPEI. Finally, at the twelve-month scale, the years with several greater intensity events were 2012, 2011, 1998 and 1989 according to the RDI, and the years 2012, 2011, 1998 and 1982 according to the SPEI.

Form the punctual analysis of the 15 more important drought events which were calculated with each of the indices for each of the 14 selected meteorological stations, it is observed that the RDI exhibits very similar intensities, regardless of whether PET is calculated with the HG or with the TW model, in the three scales of analysis. At the scales of three and six months, none of the main 15 analyzed drought events changes its category for the RDI, and at the twelve-month scale, only two events change their category. In contrast, from the analysis of the main 15 drought events detected with the SPEI, it is observed that intensities are more variable, depending on whether PET is calculated using the HG or the TW model. At the three-month scale, only one drought event detected by the SPEI changed its category, but at the scales of six and twelve months, 5 and 7 of the 15 events, respectively, changed their category depending on whether the HG or the TW model was used.

This changes in category at the scales of six and twelve months may be the result of evapotranspiration becoming a more important factor in droughts at longer time scales, because of the accumulation of deficits due to PET. As the importance of evapotranspiration grows, the effect of using different PET models also increases. The SPEI is affected more than the RDI because of its greater sensitivity to evapotranspiration.

Furthermore, at the three-month scale, the RDI detects most of the drought periods in the months from January to May, whereas the SPEI detects drought periods in the months from April to June. Regarding the six-month scale, the RDI detects most drought periods from March to June, whereas the SPEI detects them from May to September. At these scales, the SPEI detects droughts several months after the RDI. It is noteworthy that in Zacatecas, the rainy season is in the summer, when the highest temperatures also happen. The RDI, which in practice gives greater weight to precipitation, locates most droughts during the dry season, which includes the months of January and February, when temperatures are low. The SPEI detects droughts later, when temperatures and evapotranspiration are higher.

Results from this research may contribute to establishing a disaster preparedness and management plan for droughts, in order to diminish their effects on different economic sectors. Additionally, they could be useful in the implementation of subsidy programs and in insurance contracting. The use of drought assessment tools, such as drought indices, allows for proactive rather than reactive management, and thus contributes to improving resilience to droughts. Moreover, the application of drought indices in the agricultural sector of Zacatecas, and of neighboring states with similar weather, may be of great help, especially in the short term, since they would allow detecting drought conditions, and establishing drought mitigation programs, and direct assistance programs for drought – affected producers and production areas. Finally, farmers can increase their adaptive capacity to droughts through research proposals and management policies, as was pointed out by Tigkas et al. (2020).

4 Conclusions

Of the eight evapotranspiration models which were evaluated, that require a minimum input of climatological information, the Hargreaves and Samani model is considered best for estimating evapotranspiration in the state of Zacatecas, since at both daily and monthly levels, it generally provided PET estimates that were the closest to those of the reference PM model, as was shown by applying the RMSE, MAE and d efficiency indices. On the other hand, the models of Doorji and Thornthwaite are the least recommended for estimating evapotranspiration in this region, since they yielded PET estimates which differed the most from those of the PM model, at the daily and monthly scales, respectively.

The non-parametrical Wilcoxon statistical test for comparison of means leads to the conclusion that there are no statistically significant differences between the RDI and SPEI indices calculated using the TW or the HG model, in the evaluation of droughts at short, medium and long terms. Differences at the three scales of analysis (3, 6 and 12 months) of the RDI index calculated using the TW or the HG model were minimal, but are slightly greater for the SPEI, specially at the twelve-month scale. The reason why differences in drought indices calculated using TW or HG for PET estimation are not significant may be that these indices require relative temporal estimates of evapotranspiration as inputs, and that the absolute values of these estimates are not critical. Differences are greater for the SPEI than for the RDI, because of the greater sensitivity of the SPEI to evapotranspiration. Differences are also more apparent at a twelve-month scale, when PET related deficits accumulate.

For the scales of six and twelve months, the RDI gives more intense drought events than the SPEI, and in many cases, of a different category. Drought events detected by the RDI and the SPEI are more intense when the TW model is used to calculate evapotranspiration instead of the HG model. The use of the TW has a greater impact on drought intensity calculation in the case of the SPEI, specially at the three- and six-month scales. Probably this is due to how the indices are defined, whereby the RDI in practice is more sensitive to precipitation than the SPEI, and the SPEI is generally more sensitive to evapotranspiration than the RDI.

Findings from this research strengthen the idea that the RDI is a robust index for evaluating drought severity, that does not depend on the model used to calculate evapotranspiration, especially in arid and semiarid regions, at short, medium and long terms. These results may be of great importance for drought analysis in Mexico, due to the country´s climatic characteristics.

Acknowledgements The authors thank the National Meteorological Service of the National Water Commission (SMN-CONAGUA) of Mexico for providing daily rainfall data, as well as the National Institute of Forestry, Agricultural and Livestock Research for providing information of daily rainfall, maximum and minimum temperature and evapotranspiration for this study.

Declarations

Ethics Approval The authors confirm that we have fully complied with ethical standards. There is no source of funding. No participation of human or animal involvement. No financial or non-financial conflicts of interest. This article is original research and has not been published or presented previously in any journal or conference in any language.

Consent to Participate Informed consent was obtained from all individual participants included in the study.

Consent to Publish All the authors give the Publisher the permission of the authors to publish the research work.

Conflict of Interest The authors declare no competing interests.

References

Allen RG (1993) Evaluation of a temperature difference method for computing grass reference evapotranspiration. Report to Water Resources Development and Management Service Land and Water Development Division. FAO. Rome, Italy

Allen RG, Pereira LS, Raes D, Smith M (1998) Crop evapotranspiration: Guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper 56. Rome, Italy

Azhar AH, Perera B (2010) Evaluation of reference evapotranspiration estimation methods under southeast Australian conditions. J Irrig Drain Eng ASCE 137:268–279. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000297

Bayissa Y, Maskey S, Tadesse T, van Andel SJ, Moges S, van Griensven A, Solomatine D (2018) Comparison of the performance of six drought indices in characterizing historical drought for the Upper Blue Nile Basin. Ethiopia Geosci 8:81. https://doi.org/10.3390/geosciences8030081

Blaney HF, Criddle WD (1950) Determining water requirements in irrigated areas from climatological and irrigation data. Soil Conservation Service Technical Paper 96. Soil Conservation Service. Washington, US Department of Agriculture

Comisión Nacional del Agua (CONAGUA) (2018) Estadisticas del Agua en México, edición 2018. Secretaría de Medio Ambiente y Recursos Naturales. Ciudad de México

Comisión Nacional del Agua (CONAGUA) (2020) Base de datos climatológica nacional. CLIma COMputarizado (CLICOM) system. https://smn.conagua.gob.mx/es/climatologia/informacion-climatologica/informacion-estadistica-climatologica. Accessed 5 Nov 2020

Dai A (2011) Drought under global warming: a review. Wiley Interdiscip Rev Clim Change 2:45–65. https://doi.org/10.1002/wcc.81

Dorji U, Olesen JE, Seidenkrantz MS (2016) Water balance in the com- plex mountainous terrain of Bhutan and linkages to land use. J Hydrol Reg Stud 7:55–68. https://doi.org/10.1016/j.ejrh.2016.05.001

Droogers P, Allen RG (2002) Estimating reference evapotranspiration under inaccurate data conditions. Irrig Drain Sys 16:33–45. https://doi.org/10.1023/A:1015508322413

Gocic M, Trajkovic S (2010) Software for estimating reference evapotranspiration using limited weather data. Comput Electron Agric 71:158–162. https://doi.org/10.1016/j.compag.2010.01.003

Halwatura D, McIntyre N, Lechner AM, Arnold S (2017) Capability of meteorological drought indices for detecting soil moisture droughts. J Hydrol Reg Stud 12:396–412. https://doi.org/10.1016/j.ejrh.2017.06.001

Hargreaves GH, Samani ZA (1985) Reference crop evapotranspiration from temperature. Appl Eng Agric 1:96–99. https://doi.org/10.13031/2013.26773

Heim RR Jr (2002) A review of twentieth-century drought indices used in the United States. Bull Am Meteor Soc 83:1149–1165. https://doi.org/10.1175/1520-0477-83.8.1149

Hisdal H, Tallaksen LM (2003) Estimation of regional meteorological and hydrological drought characteristics. J Hydrol 281:230–247. https://doi.org/10.1016/S0022-1694(03)00233-6

Instituto Nacional de Estadística y Geografía (INEGI) (2015) Anuario estadístico y geográfico de Zacatecas 2015. Instituto Nacional de Estadística y Geografía, México

Irmak S, Irmak A, Allen RG, Jones JW (2003) Solar and net radiation-based equations to estimate reference evapotranspiration in humid climates. J Irrig Drain Eng ASCE 129(5):336–347. https://doi.org/10.1061/(ASCE)0733-9437(2003)129:5(336)

Jensen ME, Haise HR (1963) Estimating evapotranspiration from solar radiation. Proceedings of the American Society of Civil Engineers. J Irrig Drain Div 89:15–41

Khanmohammadi N, Rezaie H, Behmanesh J (2018) The spatial–temporal variation of dry and wet periods in Iran based on comparing SPI and RDI indices. Stoch Env Res Risk A 32:2771–2785. https://doi.org/10.1007/s00477-018-1594-1

López-Urrea R, de Santa M, Olalla F, Fabeiro C, Moratalla A (2006) Testing evapotranspiration equations using lysimeter observations in a semiarid climate. Agr Water Manage 85:15–26. https://doi.org/10.1016/j.agwat.2006.03.014

Makkink GF (1957) Testing the Penman formula by means of lysimeters. J Inst Water Eng 11:277–288

McEvoy DJ, Huntington JL, Abatzoglou JT, Edwards LM (2012) An evaluation of multiscalar drought indices in Nevada and eastern California. Earth Interact 16:1–18. https://doi.org/10.1175/2012EI000447.1

McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. Eight Conference on Applied Climatology. American Meteorological Society: Anaheim, CA, USA, pp 179–184

Mishra AK, Singh VP (2009) Analysis of drought severity-area- frequency curves using a general circulation model and scenario uncertainty. J Geophys Res-Atmos 114(D6):D06120. https://doi.org/10.1029/2008JD010986

Mohammed R, Scholz M (2017a) Impact of evapotranspiration formulations at various elevations on the Reconnaissance Drought Index. Water Resour Manag 31:531–548. https://doi.org/10.1007/s11269-016-1546-9

Mohammed R, Scholz M (2017b) The reconnaissance drought index: a method for detecting regional arid climatic variability and potential drought risk. J Arid Environ 144:181–191. https://doi.org/10.1016/j.jaridenv.2017.03.014

Ortiz-Gómez R, Cardona-Díaz JC, Ortiz-Robles FA, Alvarado-Medellin P (2018) Characterization of droughts by comparing three multiscale indices in Zacatecas, Mexico. Tecnol Cienc Agua 9(3):47–91. https://doi.org/10.24850/j-tyca-2018-03-03

Palmer WC (1965) Meteorological drought. Research Paper No. 45. US Department of Commerce, Weather Bureau, Washington D.C.

Penman HL (1948) Natural evaporation from open water, bare soil and grass. Proc Math Phy Eng Sci 193:120–145. https://doi.org/10.1098/rspa.1948.0037

Priestley CHB, Taylor RJ (1972) On the assessment of surface heat flux and evaporation using large scale parameters. Mon Weather Rev 100:81–92. https://doi.org/10.1175/1520-0493(1972)100%3C0081:OTAOSH%3E2.3.CO;2

Rohwer C (1931) Evaporation from free water surface. USDA Tech Null 217:1–96

Romanenko VA (1961) Computation of the autumn soil moisture using a universal relationship for a large area. In: Proceedings, Ukrainian Hydrometeorological Research Institute, No. 3. Kiev

Sheffield J, Wood EF, Roderick ML (2012) Little change in global drought over the past 60 years. Nature 491:435–438. https://doi.org/10.1038/nature11575

Tabari H (2010) Evaluation of reference crop evapotranspiration equations in various climates. Water Resour Manag 24:2311–2337. https://doi.org/10.1007/s11269-009-9553-8
Thornthwaite CW (1948) An approach toward a rational classification of climate. Geogr Rev 38:55–94. https://doi.org/10.2307/210739
Tigkas D, Vangelis H, Tsakiris G (2012) Drought and climatic change impact on streamflow in small watersheds. Sci Total Environ 440:33–41. https://doi.org/10.1016/j.scitotenv.2012.08.035
Tigkas D, Vangelis H, Tsakiris G (2020) Implementing crop evapotranspiration in RDI for farm-level drought evaluation and adaptation under climate change conditions. Water Resour Manag 34:4329–4343. https://doi.org/10.1007/s11269-020-02593-6
Tirivarombo S, Osupile D, Eliasson P (2018) Drought monitoring and analysis: Standardised Precipitation Evapotranspiration Index (SPEI) and Standardised Precipitation Index (SPI). Phys Chem Earth 106:1–10. https://doi.org/10.1016/j.pce.2018.07.001
Tsakiris G, Vangelis H (2005) Establishing a drought index incorporation evapotranspiration. Eur Water 9(10):3–11
Tsakiris G, Pangalou D, Vangelis H (2007) Regional drought assessment based on the Reconnaissance Drought Index (RDI). Water Resour Manag 21:821–833. https://doi.org/10.1007/s11269-006-9105-4
Van der Schrier G, Jones PD, Briffa KR (2011) The sensitivity of the PDSI to the Thornthwaite and Penman-Monteith parameterizations for potential evapotranspiration. J Geophys Res-Atmos 116:D03106. https://doi.org/10.1029/2010JD015001
Vangelis H, Tigkas D, Tsakiris G (2013) The effect of PET method on Reconnaissance Drought Index (RDI) calculation. J Arid Environ 88:130–140. https://doi.org/10.1016/j.jaridenv.2012.07.020
Vicente-Serrano SM, Beguería S, López-Moreno JI (2010) A multi-scalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index-SPEI. J Clim 23:1696–1718. https://doi.org/10.1175/2009JCLI2909.1
Vicente-Serrano SM, Van der Schrier G, Beguería S, Azorin-Molina C, Lopez-Moreno J-I (2015) Contribution of precipitation and reference evapotranspiration to drought indices under different climates. J Hydrol 526:42–54. https://doi.org/10.1016/j.jhydrol.2014.11.025
Yagci AL, Di L, Deng M (2013) The effect of land-cover change on vegetation greenness-based satellite agricultural drought indicators: a case study in the southwest climate division of Indiana, USA. Int J Remote Sens 34:6947–6968. https://doi.org/10.1080/01431161.2013.810824
Yuan S, Quiring SM (2014) Drought in the U.S. Great Plains (1980–2012): a sensitivity study using different methods for estimating potential evapotranspiration in the Palmer Drought Severity Index. J Geophys Res-Atmos 119:10996–11010. https://doi.org/10.1002/2014JD021970
Yue Y, Shen S-h, Wang Q (2018) Trend and variability in droughts in Northeast China based on the Reconnaissance Drought Index. Water 10:318. https://doi.org/10.3390/w10030318
Zarch MAA, Malekinezhad H, Mobin MH, Mastorani MT, Kousari MR (2011) Drought monitoring by Reconnaissance Drought Index in Iran. Water Resour Manage 25:3485–3504
Zarei AR, Mahmoudi MR (2017) Evaluation of changes in RDIst index effected by different potential evapotranspiration calculation methods. Water Resour Manag 31:4981–4999. https://doi.org/10.1007/s11269-017-1790-7
Zarei AR, Moghimi MM, Bahrami M (2019) Comparison of reconnaissance drought index (RDI) and effective reconnaissance drought index (eRDI) to evaluate drought severity. Sustain Water Resour Manag 5:1345–1356. https://doi.org/10.1007/s40899-019-00310-9
Zhang B, Wang Z, Chen G (2016) A sensitivity study of applying a two source potential evapotranspiration model in the standardized precipitation evapotranspiration index for drought monitoring. Land Degrad Dev 28:783–793. https://doi.org/10.1002/ldr.2548
Zhang B, Zhao X, Jin J, Wu P (2015) Development and evaluation of a physically based multiscalar drought index: the Standardized Moisture Anomaly Index. J Geophys Res-Atmos 120:11575–11588. https://doi.org/10.1002/2015JD023772
Zhang D, Li Z, Tian Q, Feng Y (2019) Drought assessment in a semi-arid river basin in China and its sensitivity to different evapotranspiration models. Water 11:1061. https://doi.org/10.3390/w11051061

Authors and Affiliations

Ruperto Ortiz-Gómez[1] · **Roberto S. Flowers-Cano**[2] · **Guillermo Medina-García**[3]

Guillermo Medina-García
medina.guillermo@inifap.gob.mx

[1] Universidad Autónoma de Zacatecas, Unidad Académica de Ingeniería, Ramón López Velarde 801, 98000 Zacatecas, Zac., Mexico

[2] Tabasco, Mexico

[3] Instituto Nacional de Investigaciones Forestales, Agrícolas y Pecuarias, Campo Experimental Zacatecas, Km 24.5 Carretera Zacatecas-Fresnillo, Calera, Zac., Mexico