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A Simple Model for Determining Reference Evapotranspiration Using NOAA Satellite Data: a Case Study

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Abstract Reference evapotranspiration (ET_0) is required to determine crop water requirements and irrigation scheduling. Many equations have been presented for determining ET_0 using meteorological data, but in most of these equations weather stations are located in arid lands far away from agricultural areas, and therefore, the data are not valid for estimating ET_0 . Satellite images obtain data from vast agricultural areas. In this study, the FAO-56 Penman-Monteith equation was changed to a simple linear equation with three components, and for each component, a linear regression equation was fitted to NOAA satellite data. To establish regression models and their validity, 297 NOAA satellite images over 10 years (1999 to 2008) were used. The study area was Amir Kabir Agro-Industry Irrigation Network in Khuzestan province, Iran. Results showed that the simplified model proposed in this study, estimates ET_0 with a determination coefficient of 0.92 and relative root mean square error of 8 %.

Keywords Amir Kabir Agro-Industry · Penman-Monteith FAO method · Regression model · SAS software

1 Introduction

Evapotranspiration (ET) is the outcome of all processes according to which the existing water on the surface is converted into water steam. ET is the sum of water losses caused by two processes: evaporation from soil surface and transpiration from plants. Depending on geographical location, a great percentage of annual precipitation is lost by ET. Approximately 62 % of total precipitation on earth surface returns to the atmosphere by ET (Dingman 1994; Fisher et al. 2008). Due to the close relationship between ET and energy transfer, the ET may

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essentially affect the dynamics and mobility of climate, and also fertility of global ecosystem (Fisher et al. 2008; Nishida et al. 2003). Thus, accurate determination of ET is very important for studies on water supplies and drought. Similarly, in order to manage the water supplies in farmlands and also to prevent stress on plants, estimation of the water consumed by plants is necessary.

Several models have been proposed to estimate potential evapotranspiration during the past 60 years. Some of the models have been acquired empirically based on farming experiments, which are only valid for the area where the experiments were carried out. On the other hand, models like Thornthwaite (1948), Blaney-Criddle (Blaney and Criddle 1962), Penman (1948) and others have been developed based on theoretical basis, e.g., combining the energy balance equation with mass transfer equation.

ET models can be divided into three categories: analytical (also called combination), temperature and radiation. Combination models (e.g., Penman) combine the energy driver (solar radiation) and atmospheric drivers (vapour pressure deficit and surface wind speed) to give a physically-based representation of the phenomenon. Temperature models only generally require air temperature as effective meteorological input to the model (e.g., Thornthwaite 1948; Blaney and Criddle 1962; and Hargreaves and Samani 1985). Finally, radiation models (e.g., Makkink 1957; Jensen et al. 1990; Priestley and Taylor 1972) are based on the energy balance and usually require some form of radiation measurement. The Penman -Monteith (PM) equation is one of the combination methods, which was evaluated with lysimeter data and other evapotranspiration equations from various parts of the world and showed the best accuracy (Allen et al. 1998). Due to complexities of PM equation, the FAO experts computed the elements of this equation and presented a new version of it under title of FAO-Penman-Montieth equation (FAO PM) in FAO-56 publication (Allen et al. 1998), and they suggested using this method for calculation of reference evapotranspiration (ET_0). According to the definition in FAO-56 publication, ET_0 is defined as the evapotranspiration of extensive surface of green grass of uniform height (8 to 15 cm tall), actively growing, completely shading the ground and not short of water and as a hypothetical reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s m⁻¹ and an albedo of 0.23 (Allen et al. 1998).

Considerable attention has been focused on the evaluation of the various ET_0 estimation methods. A comparison was made between six ET_0 estimation methods in a semi-arid environment by DehghaniSanij et al. (2004). The results indicated that the Penman-Monteith model produced the most reliable estimates. Tabari et al. (2013) compared pan evaporation-based and temperature-based ET_0 methods, and concluded that the Snyder and Blaney–Criddle methods yielded the best ET_0 estimates. ET_0 values obtained from the radiation-based equations developed by Tabari et al. (2013) were better than those estimated by existing radiation based methods. In another study, Fooladmand and Haghighat (2007) concluded that it is possible to estimate monthly ET_0 using the calibrated Hargreaves equation for Fars province in Iran. Tabari and Talaee (2011) demonstrated that calibration of the Hargreaves and Priestley-Taylor equations improve accuracy of ET₀ estimates. Rahimikhoob et al. (2012) evaluated the performance and characteristic behavior of four equations for estimating reference evapotranspiration (ET_0) in a subtropical climate. These equations included Makkink (1957), Turc (1961), Priestley-Taylor (Priestley and Taylor 1972), and Hargreaves (Hargreaves and Samani 1985). The results of comparison showed that the Priestley-Taylor and Hargreaves equations are more applicable in an intermediate humidity region. The performance of these equations improved slightly after calibration.

It is very difficult to calculate ET for any crop or vegetation. In practice, in order to determine ET for plants, potential evapotranspiration or ET₀ is estimated initially, and then the actual evapotranspiration of the plant (ET_a) is determined using the crop coefficient (K_C) (Allen et al. 1998). The required data for ET models are measured in meteorological stations, and are utilized practically with respect to spatial and temporal variations in the effective atmospheric parameters in the given ET process of the model close to meteorological stations (Moran and Jackson 1991). To identify ET in several zones at large scale, the density of the above stations should be at standard level so that to interpolate these models (Bussieres et al. 1997). Due to heterogeneity of zones and high variation in process of energy transfer in these regions, it is necessary to use meteorological stations with appropriate coverage and density, which is not practical and cost-effective (Nishida et al. 2003; Wang et al. 2006). Most meteorological stations in the world have been built in non-farming lands with dry weather and arid land and even adjacent to asphalt areas (Temesgen et al. 1999). This may cause errors, when compared to farmlands in calculations (Temesgen et al. 1999). The density of meteorological stations is not adequate in most areas of Iran. Even more, most of these stations are climatologic stations and present meteorological data monthly, which is not appropriate for many practical applications.

Satellite remote sensing (RS) system proposes prospective techniques for estimation of ET along with continuous spatial and temporal data. During recent years, several efforts have been made to determine ET_0 by means of satellite images. The obtained information from satellite spectral bands is used to determine the vegetation cover within visible and infrared spectra and to identify temperature of land surface within thermal spectrum. The advantages of using satellite data to determine ET is coverage of wide area, which is beneficial for regional studies, and daily analysis of ET. Nowadays some of the obtained variables using satellite data, such as the air temperature and the solar net radiation, are directly used in ET models and other data, such as land surface temperature, vegetation index and albedo, are used to estimate required parameters in evapotrainspiration models by means of correlation models. For instance, in a recent study the land surface temperature was estimated monthly with accuracy of 0.7–1.5 °C, and also in daily periods with accuracy of 2.1 °C (Sheng et al. 2009).

Recent developments in RS ET models have enabled us to accurately estimate ET for large cultivated areas and fields. Papadavid et al. (2013) integrated modeling and remote sensing techniques for estimating actual evapotranspiration of groundnuts that is cultivated near Mandria Village in Paphos District of Cyprus. During the last two decades, many energy balance (EB) algorithms have been developed to make use of RS data to estimate ET regionally. These algorithms compute at satellite overpass instantaneous ET as the residual term of energy budget, once net radiation, soil heat flux and sensible heat flux are derived (Bastiaanssen et al. 1998a; Norman et al. 2003; Su 2002; Caparrini et al. 2003, 2004; French et al. 2005; Crow and Kustas 2005; Allen et al. 2007; Cleugh et al. 2007). A detailed review of different ET algorithms was presented in Gowda et al. (2008). Some of the commonly used EB-based ET algorithms include Surface Energy Balance Algorithm for Land (SEBAL; Bastiaanssen et al. 1998a, 1998b), Surface Energy Balance Index (SEBI; Menenti and Choudhury 1993), Surface Energy Balance System (SEBS; Su 2002), and most recently, the Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC; Allen et al. 2007) method. Elhag et al. (2011) used the SEB System to estimate daily evapotranspiration and evaporative fraction over the Nile Delta. The simulated daily evapotranspiration values were compared against actual ground-truth data taken from 92 points uniformly distributed all over the study area. They showed that SEBS could successfully be employed in the estimation of daily evapotranspiration over agricultural areas. However, above mentioned algorithms are complex to use and they calculate actual ET rather than reference ET (ET₀). The estimate of ET₀ is an important factor to be considered in agricultural planning and has been an objective of studies related to irrigation management and agrometeorology all over the world. It is desirable to have a method that estimates ET₀ from a large irrigated farm surface. The combination of ET₀ models with RS data provides a feasible alternative to obtain temporally and spatially continuous information about biophysical variables (Maeda et al. 2011). Maeda et al. (2011) evaluated three temperature-based ET₀ models by using land surface temperature data from the MODIS sensor that is replaced by air temperature data from ground stations. This evaluation has been conducted in an intertropical convergence zone. They showed that Hargreaves model is the most appropriate with an average RMSE of 0.47 mm d⁻¹, and a correlation coefficient of 0.67. In this paper, we have proposed a simple equation to estimate reference evapotranspiration from the NOAA satellite data.

2 Materials and Methods

2.1 FAO Penman-Monteith Equation Simplification

In order to calculate ET_0 , FAO has presented the following equation in its FAO-56 publication (Allen et al. 1998):

$$ET_0 PM = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_a + 273} U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)}$$
(1)

where ET_0 PM is reference crop evapotanspiration calculated using the FAO PM method (mm d⁻¹), R_n is the daily net radiation (MJ m⁻² d⁻¹), G is the daily soil heat flux (MJ m⁻² d⁻¹), T_a is the mean daily air temperature at a height of 2 m (°C), U₂ is the daily mean wind speed at a height of 2 m (m s⁻¹), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), Δ is the slope of the saturation vapor pressure versus the air temperature curve (kPa °C⁻¹), and γ is the psychrometric constant (kPa °C⁻¹). The terms in the numerator on the right-hand side of the equation are the radiation term and aerodynamic term, respectively. For daily periods, the value of G is considered to be zero (Allen et al. 1998). Eq. (1) can also be written as:

$$ET_0 = A R_n + B \tag{2}$$

where components A and B are as follows:

$$A = \frac{0.408\Delta}{\Delta + \gamma(1 + 0.34U_2)} \tag{3}$$

$$B = \frac{\gamma \frac{900}{T_a + 273} U_2(e_s - e_a)}{\Delta + \gamma (1 + 0.34 \ U2)}$$
(4)

In this study, it was assumed that each of the components A, R_n and B are a function of five channels of the NOAA satellite. Therefore, in this study, the hypothesis was tested that linear

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relationships can be created between these components and five channels of NOAA satellite images. In other words, A, R_n and B can be estimated instead of weather data. The main purpose of this study was assessing this assumption. The Daily components A, R_n and B were estimated by meteorological data from a weather station in an irrigation network located in Khuzestan province in Iran for a 10-year period from 1999 to 2008. The daily values of γ , Δ , R_n , e_s and e_a . were calculated using the equations given by Allen et al. (1998). The estimated components by meteorological data were used as reference data for creating and testing functions with inputs of NOAA satellite channels.

2.2 Estimating Net Radiation Using FAO-56 Methodology (FAO56-R_n)

Allen et al. (1998) in the FAO Irrigation and Drainage Paper No. 56, proposed a method for calculating R_n (this method is referred to hereafter as FAO56- R_n). Accordingly, for obtaining R_n based on FAO56- R_n method, relative humidity (RH), sunshine duration (n) or solar radiation (R_s) and air temperature (T) should be measured in the meteorological stations. They also recommended using Angstrom formula (Ångström 1924) when R_s is restricted. Angstrom formula relates R_s to extraterrestrial radiation and relative sunshine duration. Extraterrestrial radiation can be calculated theoretically for a certain day and location; therefore, only actual duration of sunshine needs to be measured in the meteorological station.

In this work, the performance of the created model was compared with the well known FAO-56 methodology proposed by Allen et al. (1998) that uses incident solar radiation, relative humidity and temperature data for the assessment of R_n . In FAO-56 methodology, R_n is calculated as the difference between incoming net short-wave radiation (R_{ns}) and the outgoing net long-wave radiation (R_{nl}). The net short-wave radiation results from the balance between incoming and reflected solar radiation. The model created in this study for estimating R_n was calibrated and tested using the conventional FAO-56 methodology. The FAO56- R_n equations for calculating daily R_{ns} , R_{nl} , and R_n can be expressed, respectively, as follows:

$$\mathbf{R}_{\rm ns} = (1 - \alpha) \times \mathbf{R}_{\rm s} \tag{5}$$

$$R_{nl} = \left[\sigma\left(\frac{T_x^4 + T_n^4}{2}\right)(0.34 - 0.14\sqrt{e_a})\left(1.35\frac{R_s}{R_{so}} - 0.35\right)\right]$$
(6)

$$\mathbf{R}_{\mathrm{n}} = \mathbf{R}_{\mathrm{ns}} - \mathbf{R}_{\mathrm{nl}} \tag{7}$$

where R_{ns} is the net short-wave radiation (MJ m² d⁻¹); α is the albedo of the surface (= 0.23 for green vegetation surface); R_{nl} is the net long-wave radiation (MJ m² d⁻¹); R_s is the incoming solar radiation (MJ m² d⁻¹); σ is the Stefan–Boltzmann constant (4.903 × 10⁻⁹ MJ K⁻⁴ d⁻¹); T_x is maximum absolue temperature during the 24-h period in Kelvin (=°C + 273.16); T_n is minimum absolute temperature during the 24-h period in Kelvin (=°C + 273.16); e_a is the actual vapour pressure (kPa); R_{so} is the clear sky radiation (MJ m² d⁻¹) and R_s/R_{so} is the relative shortwave radiation (limited to ≤1). Three models were proposed by Allen et al. (1998) to compute the parameter e_a according to the available weather data. In this study, measured

 RH_m , T_x , and T_n values were used to calculate e_a . The clear sky radiation R_{so} was calculated from the following equation (Allen et al. 1998):

$$R_{so} = (0.75 + 2 \times 10^{-5} \times Z) R_a$$
(8)

where Z is station elevation above sea level (=22.5 m in Ahvaz station) and R_a is the extra terrestrial radiation (MJ m² d⁻¹). The daily extra terrestrial radiation R_a was calculated as (Allen et al. 1998):

$$\mathbf{R}_{a} = (24 \times 60/\pi) \times \mathbf{G}_{sc} \times \mathbf{d}_{r}[\omega_{s}\sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\sin(\omega_{s})]$$
(9)

where, G_{sc} is the solar constant (=0.0820 MJ m² d⁻¹), d_r is the inverse relative distance between Earth-Sun, Ω_s is the sunset hour angle (radians), φ is the latitude of the site (radians) and δ is the sun declination (radians). d_r is computed using the following equation by Duffie and Beckman (1980), also given in Allen et al. (1998):

$$d_{\rm r} = 1 + 0.033\cos(2\pi/365 \times J) \tag{10}$$

where J is the sequential day of the year (starting 1 January) and the angle ($J \times 2\pi/365$) is in radians. Values for d_r range from 0.97 to 1.03 and are dimensionless. δ and Ω_s were calculated by the following equations (Allen et al. 1998):

$$\delta = 0.409 \sin \left\{ (2\pi/365 \times J) - 1.39 \right\}$$
(11)

$$\omega_{\rm s} = \arccos[-\tan(\varphi) \times \tan(\delta)] \tag{12}$$

where all the variables have been previously defined. In this study, the daily solar or shortwave radiation (R_s) was calculated using the Angstrom formula, which relates solar radiation to extraterrestrial radiation and relative sunshine duration (Allen et al. 1998):

$$R_{s} = \left(a + b\frac{n}{N}\right)R_{a} \tag{13}$$

where n and N are, respectively, the actual daily sunshine duration and the daily maximum possible sunshine duration, R_s and R_a are, respectively, the daily global solar radiation (MJ m⁻² d⁻¹) and the daily extraterrestrial solar radiation (MJ m⁻² d⁻¹) on a horizontal surface, and a and b are empirical coefficients which depend on location. Allen et al. (1998) recommended using a = 0.25 and b = 0.5 in cases where no actual solar radiation data are available and no calibration has been carried out for improved a and b parameters. We used the default values of these parameters proposed by Allen et al. (1998), due to non- availability of actual solar radiation data in this study.

2.3 Study Area and Climate Dataset

The present investigation has been carried out in the Amir Kabir Agro-Industry Irrigation network in Khuzestan Proviance, Iran with an area of 14,000 ha. This region is located 45 km south of Ahvaz city that is on the right bank of the Karun River with coordinates $48^{\circ}12'$ to $48^{\circ}20'$ east and $30^{\circ}57'$ to $31^{\circ}05$ north. The area is devoted to the cultivation of sugar cane. Among all pixels of this network, those that represented the maximum evapotranspiration were selected and their channel characteristics were used to determine the components A, R_n and B.

Figure 1 is a NOAA satellite image showing the location of Amir Kabir Agro-Industry Irrigation network. Measured weather data were obtained from one weather station which is located within the irrigation network. In this regard, the daily meteorological data for a period of 10 years from 1999 to 2008 were colleccted. These data consisted of maximum and minimum air temperature, relative humidity, wind speed and sunshine duration. The annual averages of these parameters are given in Table 1. Data integrity was evaluated using methods similar to those suggested by Allen (1996).

2.4 NOAA Satellite Data

Advanced Very High Resolution Radiometer (AVHRR) in NOAA satellite measures the reflected radiation and emitted heat from the land surface in five spectral channels including visible band (0.58–0.68 μ m), near infrared (0.725–1.10 μ m), medium infrared (3.55–3.98 μ m), and two thermal infrared bands (10.3–11.3 and 11.5–12.5 μ m). The dimensions of NOAA satellite image pixels were 1.21 km² in nadir point for all the bands. The satellite on a given area takes image twice per 24 h period (once at day time and once at night time). Since land cover and surface temperature affect net radiation and evapotranspiration, we used all five channels obtained from NOAA-AVHRR sensor for converting them to A, R_n and B components.

In this study, 297 daily NOAA satellite images with no cloud cover for a period of 10 years (1999 to 2008) were obtained (www.class.ncdc.noaa.gov). These images were scanned between noon and 3.00 pm (local time) in 1999–2008. NOAA satellite image files contained digital numbers of pixels, calibration coefficients and a series of satellite ground and orbital control points coordinates. Calibration coefficients were used for converting digital



Fig. 1 Location of the Amir Kabir Agro-Industry Irrigation network used for the study

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Air temperature (°C)			Relative humidity (%)			wind speed (m s ⁻¹)	precipitation (mm)		
Max	Min	Av.	Max	Min	Av.				
49.6	-0.4	24.9	99.8	2.41	44.4	3.2	168		

Table 1 Mean annual values of the meteorological parameters during the period of 1999-2008

numbers of 1 and 2 visible bands into albedo (in %) and bands 3, 4 and 5, into temperature (in degrees Kelvin). Coordinates of ground control points were used to correct geometric images. Albedo value depends on the sun angle and the angle changes in the hours and days of year. In order to represent the surface reflection, this parameter is normalized according to the solar zenith angle. All the above-mentioned analysis, such as digital number calibration, image geometric correction and normalization of albedo of bands 1 and 2, were carried out using the ENVI version 4.2 software.

2.5 Normalized Difference of Vegetation Index

One of the most common vegetation indices that is estimated using satellite image data is the normalized difference of vegetation index (NDVI), which is closely related to vegetation cover and leaf area index (LAI) (John et al. 1998). Because of normalizing the difference of near-infrared and red bands, this index has minimal atmospheric effects and its efficacy to monitor plant growth and changes has been proved (Julien et al. 2006). NDVI is based on the fact that a healthy vegetation in the visible range of the electromagnetic waves (0.4 to 0.7 μ m) due to the absorption of chlorophyll and other pigments reflects a little, but reflects significantly in the infrared range (0.7 to 1.05 μ m) due to the spongy tissue of the mesophile leaf surface (Cambell 2002). The following formula was used to determine NDVI:

$$NDVI = \frac{ch2 - ch1}{ch2 + ch1}$$
(14)

In the above equation, ch1 and ch2 are calibrated values of the visible and infrared reflects of 1 and 2 bands of NOAA satellite AVHRR sensor, respectively. Theoretically NDVI is between -1 to +1. In lands with vegetation, NDVI is between 0.1 and 1. In areas with dense, healthy and fully irrigated vegetation, the NDVI value approaches 0.7. In areas without plants, NDVI is negative. NDVI value in barren lands is less than 0.2, in lands with moderate vegetation is between 0.2 and 0.5, and in lands with dense vegetation, as mentioned, is greater than 0.5 (Julien et al. 2006).

2.6 Selecting the Pixel Representing ET₀

The originality of this paper is to use cold pixel from large irrigated sugarcane farms surface. The cold pixel was selected as a wet, well-irrigated crop surface, having full ground cover by vegetation with maximum ET occurring at this surface. For each image, one polygon was defined around the Amir Kabir irrigation network. As mentioned above, this network consists of well-vegetated areas, but for ensuring the right choice of pixels to represent the reference evapotranspiration, the pixel with the highest NDVI within the polygon was selected. This pixel was represented as "cold" pixels and its five channels of the AVHRR image (C1-C5)

were used together with the days of year (DOY) as inputs to the functions for estimating R_n , A and B components.

In order to determine the cold pixel, for each image using the Pixel to Table option from Utility menu of ERDAS IMAGINE software, all pixel Information within Amir Kabir irrigation network were transferred to a text file. The NDVI for all pixels were calculated in Excel software using 1 and 2 band values and the NDVI with the highest value for each image was found. This pixel was chosen as the reference for determining ET_0 and its information was extracted.

2.7 Regression Models

Using stepwise regression model for each of the components in Eq. (2) (R_n , A and B), functions from the independent variables consisting of five bands of reference pixel (C1 to C5) and days of year (DOY) variable were selected. DOY variable were used to consider the effect of seasonal changes on ET₀. In stepwise model, the most effective independent variables were selected and the rest of the variables were deleted. SAS software was used, in order to determine the significance of the regression model coefficients. FAO PM model was chosen as a reference model for assessing the performance of the Eq. (2). In this study, the data from 1999 to 2006 were collected into one set to create regression models. This data set had a total of 216 patterns. After the creating process, the remaining data (2007 and 2008) were used to test regression models. The test data set had a total of 81 patterns that were not used for creating process.

2.8 Statistical Analysis

In this study, the result of calculated parameters Rn, A, B and ET_0 by using weather station data were used as observed values and the result of prediction of these parameters by NOAA satellite data and regression models were used as predicted values. The performance of the regression models and evaluation of estimates Rn, A, B and ET_0 from NOAA satellite data were checked with four statistical indices: determination coefficient (R²), mean bias error (MBE), root mean square error (RMSE) and relative root mean square error (RelRMSE). These indices are defined as follows:

$$R^{2} = \frac{\left[\sum \left(\mathbf{P}_{i} - \overline{\mathbf{P}}\right) \left(O_{i} - \overline{\mathbf{O}}\right)\right]^{2}}{\sum \left(\mathbf{P}_{i} - \overline{\mathbf{P}}\right)^{2} \sum \left(O_{i} - \overline{\mathbf{O}}\right)^{2}}$$
(15)

$$RMSE = \left[N^{-1} \sum_{i=1}^{N} (O_i - P_i)^2 \right]^{0.5}$$
(16)

$$MBE = \frac{\sum_{i=1}^{N} (P_i - O_i)}{N}$$
(17)

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$$RelRMSE = \frac{RMSE}{\overline{O}} \times 100$$
(18)

where O_i is the observed value, P_i is the predicted value, N is the number of observations and the overbar is an averaging operator.

3 Results and Discussion

Stepwise regression model was used to create regression models for estimating Rn, A and B. In this case, the whole set of creating data (data from 1999 to 2006) were used. The following relationships were found:

$$R_n = 14.668 - 0.00041 (DOY - 175)^2$$
⁽¹⁹⁾

$$A = -1.288 + 0.0049 C3 + 0.00015 DOY$$
(20)

$$B = -73.659 + 0.032 C2 + 0.15 C3 + 0.103 C5$$
(21)

These equations show that among the six independent variables, only DOY had significant impact on R_n and the other variables were omitted in the modeling process. For component A, the variables band 3 of NOAA satellite (C3) and DOY, and for component B, the variables bands 2, 3 and 5 of NOAA satellite (C2, B3 and C5) are effective. Analysis of variance of Equations (10) to (12) are presented in Table 2. According to the variance analysis shown in Table 2, effective factors in regression modeling process are selected in the model in order of their priority. Therefore, the most effective factors in predicting parameters A and B is band 3 of NOAA satellite (C3). Analysis of variance was also significant at probability levels of 1 % by means of F-test.

Satellite data of two test years (2007 to 2008) were used in Equations (19) to (21). The obtained results are compared with results of components Rn, A and B calculated from meteorological data in Fig. 2. As it can be seen from this figure, the slope of the straight line of the three regression equations are close to 1 which indicates that there is good fit between the measured components Rn, A and B and those estimated by the regression models. The summary of the statistic calculations in order to estimate the components of simplified FAO PM Equation is presented in Table 3. Among the models shown in Table 3, the regression model of net radiation (R_n) with determination coefficient of 0.94 and relative error of 7.12 % has the highest accuracy, and the B regression model with determination coefficient of 0.83 and relative error of 16.17 % has minimum accuracy. Mean bias error of 0.01 in R_n model and -0.01 in B model indicate that overestimation and underestimation in models are insignificant.

The ET_0 values estimated by the proposed method (Eq. 2) were compared with FAO PM estimates for testing data set. The proposed method was taken as independent variable and the estimations made using FAO PM method as the dependent variable. The test data set had a total of 81 days (daily weather data from 2007 and 2008) that were not used in the development.

Figure 3 shows a comparison of Eq. (2) and FAO PM in a 1.1 plot for two years test. The statistical indices presented in the graph were used to evaluate the performance of Eq. (2). As Fig. 3 shows, there is a very good correlation between the ET_0 computed with the simplified

Parameter	Step	Variable	Variable estimation	Source of Variation	Degree of freedom (DF)	Sum of squares (SS)	Man square (MS)	R ²	Variance Inflation
R _n		Intercept	14.668						
				Model	1	2102.81	2102.81**		
	1	(DOY-175) ^{^2}	-0.00041	Error	193	148.62	0.77	0.93	1.00
				Total	194	2251.43			
А		Intercept	-1.288						
				Model	1	0.36	0.36**		
	1	B3	0.0049	Error	207	0.15	0.00	0.71	1.00
				Total	208	0.50			
				Model	2	0.39	0.20**		
	2	doy	0.00015	Error	206	0.11	0.00	0.79	1.00
				Total	208	0.50			
В		Intercept	-73.659						
				Model	1	824.27	824.27**		
	1	В3	0.150	Error	192	271.03	1.41	0.75	7.61
				Total	193	1095.30			
				Model	2	840.34	420.17**		
	2	В5	0.103	Error	191	254.96	1.33	0.77	7.63
				Total	193	1095.30			
				Model	3	853.57	284.52**		
	3	B2	0.032	Error	190	241.73	1.27	0.78	1.01
				Total	193	1095.30			

Table 2 Variance Analysis of the estimated parameters

**denotes analysis of variance is significant at probability levels of 1 %

equation. The slope of the straight line in the proposed model (=1.02 and 0.98 for years 2007 and 2008, respectively) is very close to one. All ET_0 data appear to be well distributed along the 1:1 line and do not introduce a bias in ET_0 estimations. The MBE for 2007 and 2008 were -0.08 and 0.09 mm d⁻¹, respectively, therefore, neither overestimations nor underestimations are produced in the range of the values studied. The high values of R² (=0.92 for both test years) show that approximately 92 % of the variations in the simplified PM model are linearly related to the FAO PM model. The RMSE is generally low (0.66 and 0.63 mm d⁻¹ for the two years, and equivalent to a relative error under 8.2 %) indicating that for the proposed method the systematic error is small. Figure 4 shows the variation in reference evapotranspiration estimated using the FAO-PM method and the simplified equation (Eq. 2) during the test period. It can be seen that both models have no significant MBE. In both models, the evolution is similar and one line of data is practically superimposed over the other.

4 Conclusions

The FAO Penman-Monteith equation was simplified into three components. For each component a regression model was obtained from six independent variables of five



Fig. 2 Comparative results of the estimated parameters R_n , A and B from meteorological data and those estimated by the proposed models (Eqs. 19–21), using testing data set

NOAA Satellite bands data and DOY (day of the year) parameter using step by step regression modeling method at probability level of 1 % by means of F-test. The results showed that among six independent variables, the DOY parameter with determination coefficient of 0.94 is the only significant factor to determine the net radiation (R_n) in the net radiation regression model. Considering that the net radiation for an area is a great deal depending on atmospheric conditions such as humidity and cloud covering, the obtained regression model is only applicable in this area of study. The regression model of component A was dependent on the third NOAA satellite band (C3) and DOY parameters, showing a determination coefficient of 0.87. The significant variables in

Table 3	Statistical summary of the estimated R _n , A and B parameters by FAO56 method	l against those obtained
by the re	gression models, for creating and testing data set	

Parameter	Creating data set				Testing data set			
	R ²	RMSE mm d ⁻¹	MBE mm d ⁻¹	RelRMSE (%)	R ²	RMSE mm d ⁻¹	MBE mm d ⁻¹	RelRMSE (%)
R _n	0.93	0.87	-0.02	7.57	0.94	0.80	0.01	7.12
А	0.79	0.02	0.00	9.53	0.87	0.02	0.00	7.13
В	0.78	1.11	-0.01	22.82	0.83	0.86	-0.01	16.71



Fig. 3 Scatter plot between ET_0 estimated by FAO-PM method and simplified equation (Eq. 2) during the test period (2007 and 2008)

the regression model of component B also turned out to be the two, three and five NOAA satellite bands (C2, C3 and C5) with determination coefficient of 0.83.

The ET_0 was estimated in Amir Kabir agro-industry irrigation network using regression models with determination coefficient of 0.92 and average error of 0.6 mm per day. As the simplified evapotranspiration model in this study estimates evapotranspiration using regression models, this model can be used only in the vicinity of Amir Kabir irrigation network, while for



Fig. 4 Evolution of ET_0 estimated by FAO-PM and those estimated by simplified equation (Eq. 2) during the test period (2007 and 2008). Vertical dashed lines delineate the beginning of each season

other irrigation networks it should be calibrated based on meteorological data of that region. It should be noted that only data from cold pixels located in the irrigated area were used in this analysis, therefore the relationships are only valid for these cold pixels located in Amir Kabir agro-industry irrigation network and not necessarily for the entire area.

Conflict of Interest We have no conflict of interest to declare.

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