

Original Research Article

<https://doi.org/10.20546/ijcmas.2019.807.255>

Impact of Metrological Parameters on Reference Evapotranspiration using Multiple Linear Regressions

Yadvendra Pal Singh*, H.K. Mittal, P.K. Singh, S.R. Bhakar and H.K. Jain

Department of Soil & Water Engineering at Maharana Pratap University of Agriculture & Technology, Udaipur (Rajasthan), India

*Corresponding author

ABSTRACT

The reference evapotranspiration (ET_0) of Morena station was estimated using multiple linear regression (MLR). The climatological data such as maximum temperatures, minimum temperature, mean relative humidity, wind speed and solar radiation were collected for the morena station and district of Madhya Pradesh state of India for the period of thirty years and the missing value of that data series was also determined using SPSS-21 software. The observed reference evapotranspiration (ET_0) values were estimated using the Penman monteith (FAO56-PM) equation. Multiple Linear Regression is carried out using ET_0 as predictor variable and maximum temperatures, minimum temperature, relative humidity, solar radiation and wind speed as independent variable to find out predominant factor on ET_0 . This whole procedure is done for three different variable based Models. In model-1, Maximum temperature and minimum temperature speed are correlated with ET_0 . In model-2, Maximum temperature, minimum temperature and solar radiation are correlated with ET_0 . In model-3, Maximum temperature, minimum temperature, mean relative humidity and wind speed are correlated with ET_0 . In case of model 3 the value of R, R^2 and RMSE for 70% dataset is 0.975, 0.949 and 0.466 respectively and for 30% dataset it is 0.981, 0.962 and 0.607 respectively. As the value of R and R^2 are nearer to 1 and the value of RMSE is low, which is good. As the model-3 gives the best correlation values as compared to model-2 and model-1, it can be accepted as the best fit model for prediction of ET_0 . Considering maximum temperature the model gives good correlation values hence maximum temperature is accepted as predominant factor and the presence of relative humidity does not play an important role in prediction of ET_0 for this study area.

Keywords

Multiple linear regression, Performance evaluation, Climate change and reference evapotranspiration

Article Info

Accepted:
17 June 2019
Available Online:
10 July 2019

Introduction

India is more susceptible to effect of climate change due to its high dependence on climate sensitive sectors such as forestry and agriculture (Mahida and Palel, 2015). According to the IPCC (2007), the average

global surface temperature increased by 0.74°C over the last 100 years. General agreement have revealed that global warming and related changes to the hydrological cycle are likely to enhance the frequency and severity of extreme climate events, causing more severe floods and droughts. Global

warming due to the enhanced greenhouse effect is expected to cause major changes in various climatic variables, such as precipitation, relative humidity, solar radiation and temperature. Atmospheric temperature is the most widely used indicator of climatic changes as global and regional scales, and global land-surface air temperatures have increased in the Northern Hemisphere by 0.3°C/ decade from 1979 to 2005.

The combination of two separate processes, where water is lost from the soil surface by evaporation and from the crop by transpiration, is called as evapotranspiration. Hydrological parameters such as precipitation, evapotranspiration, soil moisture and ground water are likely to change with climate (Gleick, 1986), and the impact of climate change on evapotranspiration rate is important for hydrologic processes. Crop water requirements depend upon several climatic variables like rainfall, radiation, temperature, humidity and wind speed. Therefore, any change in climatic parameters due to global warming will also affect evapotranspiration (Goyal, 2004). An indirect way to obtain estimates of evapotranspiration is the evaporation rate from pans filled with water, known as pan evaporation (Epan). Trends in Epan have been reported with different conclusions depending on the region studied. Jhajharia (Jhajharia *et al.*, 2009) found both decreasing and increasing tendencies in Epan in northeast India, depending on the location of the station. Decreases in Epan have been attributed to decreasing surface solar radiation and wind speed (Xu *et al.*, 2006) and increases in cloud cover, greater air pollution and higher concentrations of atmosphere aerosols. Pan evaporation depends on the water surface temperature and energy balance between the evaporation pan, water and the atmosphere. If the humidity does not change,

increasing water temperature should increase evaporation. If the humidity increases, it will partially offset the impact of higher temperature on the evaporation. Small changes in evapotranspiration can have important consequences in arid climates. 1% temperature increase could increase evapotranspiration by 12.69% in arid regions of Rajasthan, India, where the annual rainfall varies from 100 to 400 mm and mean temperature varies by about 25°C (Goyal, 2004).

Reference crop evapotranspiration (ET_0) refers to crop evapotranspiration in the open short grass land where the soil moisture is adequate, ground is completely covered, grass grew normally with the similar height (grass height is about 8-15 cm) (Allen *et al.*, 1998). ET_0 is the most important parameter while predicting the crop water requirement. In the context of climate change, changes of temperature, wind speed, rainfall, solar radiation and other factors will lead to the change of ET_0 , thus affecting the crop water demand and agricultural water usage. In the context of climate change, changes of temperature, wind speed, rainfall, solar radiation and other factors will lead to the change of ET_0 , thus affecting the plan of crop water demand and agricultural water usage.

Materials and Methods

Study area and data collection

Morena is a district of Madhya Pradesh state is located at 78°00' E longitude, 26°30' N latitude at an altitude of 177 m above mean sea level.

The daily meteorological data such as maximum temperature, minimum temperature, solar radiation, mean relative humidity and wind speed for the Morena station were collected and used in the data

analysis and model development. The monthly average metrological data for the thirty years has been used for this study.

Methodology

In this study, daily metrological data for the morena station were collected. These data has been converted into the monthly average data. Some data gaps or missing values are indentified in data. The missing values were found out with the SPSS 21 software. The linear trend at a point method is used to find the missing values of the data. To study the impact of metrological data on reference evapotranspiration (ET₀) multiple linear regression analysis was performed. The observed ET₀ values have been estimated using the general equation of evapotranspiration (FAO-56).The equation is;

According to Allen *et al.*, (1998), recommended form of FAO56-PM model consisting of aerodynamic and surface resistance terms is:

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

Where,
ET₀ is reference evapotranspiration (mm d⁻¹), R_n is net radiation at crop surface (MJ m⁻² d⁻¹), G is soil heat flux density (MJ m⁻² d⁻¹), T_{av} is mean daily air temperature (oC), U₂ is wind speed at 2 m height (m s⁻¹), e_a is actual vapour pressure (kPa), e_s is saturation vapour pressure (kPa), e_s-e_a is vapour pressure deficit (kPa), Δ is slope of vapour pressure curve (kPa oC⁻¹), and γ is psychrometric constant (kPa oC⁻¹).

Multiple linear regression (MLR) model

The objective of the model is the transfer of information among several variables observed simultaneously and the estimation of the

dependent variable from the several other observed independent variables. The monthly reference evapotranspiration (ET₀) at a meteorological data is expressed as a simple linear model as

$$ET_0 = S + a_1 X_1 + a_2 X_2 + a_3 X_3 + a_4 X_4 + a_5 X_5 \dots (2)$$

Where, a₁, a₂a_n and S are empirical constants and X₁, X₂.....X_n are the meteorological parameters influencing the region.

Now, MLR is carried out using ET₀ as dependent variable and maximum temperature, minimum temperature, relative humidity, wind speed and solar radiation as independent variable to find out predominant factor on ET₀ and obtain best model.

This whole procedure is repeated for three different Models.

In Model 1, Maximum temperature and minimum temperature are correlated with ET₀.

In Model 2, Maximum temperature, minimum temperature and solar radiation are correlated with ET₀.

In Model 3, Maximum temperature, minimum temperature, mean relative humidity and wind speed are correlated with ET₀.

This entire data set is divided into two datasets 70% data for training and 30% data for validation. Then, the corresponding co-efficient of correlation (R) for training and testing data set is evaluated.

Performance evaluation parameters

The performance evaluation parameters used in the present study are the Pearson

correlation coefficient (R), coefficient of determination (R^2) and root mean square error (RMSE).

Correlation coefficient (R)

Correlation – often measured as a correlation coefficient which indicates the strength and direction of a linear relationship between two variables (for example model output and observed values). A number of different coefficients are used for different situations. The formula to find out the correlation coefficient is;

$$R = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$$

The correlation is +1 in the case of a perfect increasing linear relationship and -1 in case of a decreasing linear relationship, and the values in between indicates the degree of linear relationship between model and observations. A correlation coefficient of 0 means there is no linear relationship between the variables.

The square of the Correlation coefficient (R^2), known as the coefficient of determination,

The coefficient of determination, R^2 , is useful because it gives the proportion of the fluctuation of one variable that is predictable from the other variable. It is a measure that allows determining how certain one can be in making predictions from a certain model/graph. The coefficient of determination is such that $0 < R^2 < 1$, and denotes the strength of the linear association between x and y.

The coefficient of determination represents the percent of the data that is the closest to the line of best fit.

Root mean square error (RMSE)

The Root Mean Square Error (RMSE) is used to measure the difference between predicted values by a model and the actually observed values from the location. These individual differences are also called residuals. The RMSE of a model prediction with respect to the estimated variable X_j is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}}$$

Where, X_i is observed values and X_j is modeled values at time/place i.

The RMSE values can be used to distinguish model performance in calibration period with that of a validation period as well as to compare the individual model performance to that of other predictive models.

RMSE ranges from zero to infinity and its lower values are preferable.

Results and Discussion

In this study the performance evaluation parameters such as R, R^2 and RMSE has been calculated for the two stages i.e. training and validation for each model and are given in Table 1.

Referring to the table 1, in case of model 1 the value of R, R^2 and RMSE for 70% dataset is 0.975, 0.949 and 0.466 respectively and for 30% dataset it is 0.981, 0.962 and 0.607 respectively, which is very good. In case of model -2 the value of R, R^2 and RMSE for 70% dataset is 0.954, 0.908 and 0.635 respectively and for 30 % dataset it is 0.956, 0.913 and 0.814 respectively, which is comparatively good. In case of model-1 the value of R, R^2 and RMSE for 70% dataset is 0.949, 0.898 and 0.657 respectively and for

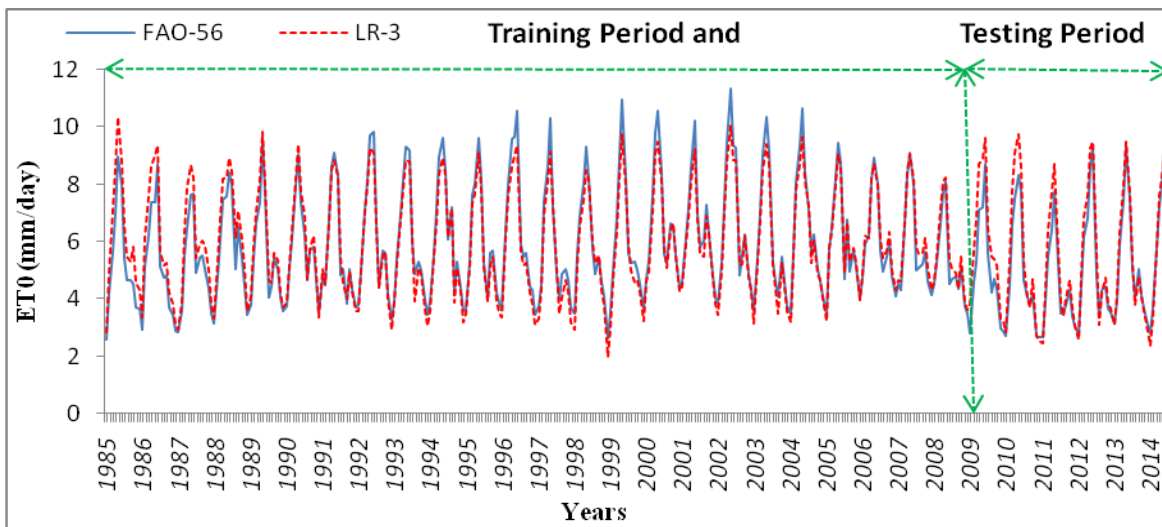
30% dataset it is 0.956, 0.914 and 0.735 respectively, which is comparatively low. Here, it is easily noticeable that while, considering maximum temperature coefficient of correlation achieved as the best. From the above exercise one can observed that value of maximum temperature is significantly affecting the value of ET₀ as compared to the value of solar radiation,

relative humidity and wind speed. Addition of Relative Humidity does not perform important task. Considering the all models, model 1 gives the best correlation values Hence, It is accepted as best fit model. The Figure 1 show the plot of observed ET₀ vs. predicted ET₀ for training and validation respectively for model 1.

Table.1

| MOD EL | R | | R ² | | RMSE | |
|-----------|--------------|--------------|----------------|--------------|--------------|--------------|
| | Training | Testing | Tannin g | Testing | Trainin g | Testin g |
| 1 | 0.949 | 0.956 | 0.898 | 0.914 | 0.657 | 0.735 |
| 2 | 0.954 | 0.956 | 0.908 | 0.913 | 0.625 | 0.814 |
| 3 | 0.975 | 0.981 | 0.949 | 0.962 | 0.466 | 0.607 |

Fig.1 Comparison of the value of ET₀ by PM-56 model and LR-3 (Tmax, Tmin, U₂ and RH) models



Comparing results of all five models, following are the conclusions:

In case of model 3 the value of R and R² are nearer to 1 and the value of RMSE is low, which is good.

In case of model-2 the value of R and R² are nearer to 1 but lower than model-3 and also, the value of RMSE is higher than model-1. Hence the model can't be accepted as best fit model.

In case of model 1 the value of R and R² are nearer to 1 and higher than model-2, also the value of RMSE is less compared to model-2.

As the model 3 gives the best correlation values as compared to model 2 and model 1, it can be accepted as the best fit model for prediction of ET₀. When considering maximum temperature the model gives good correlation values hence maximum temperature is accepted as predominant factor and the presence of relative humidity does not play an important role in prediction of ET₀ for this study area.

References

- Allen, R. G, Pereira L. S, Raes, D. and Smith M, (1998) Crops evapotranspiration. Guidelines for computing crop requirements. Irrigations and Drainage Paper 56. FAO, Rome.
- Gleick, P. H., (1986) Methods for evaluating the regional hydrologic impacts of global climatic changes. *J. Hydrol.* 88: 97–116.
- Goyal, R. K., (2004) Sensitivity of evapotranspiration to global warming: a case study of arid of Rajasthan (India). *Agric Water Manag.* 69, 1–11.
- Jhajharia, D., Shrivastava, S. K. Sarkar, D. and Sarkar, S., (2009) Temporal characteristics of pan evaporation trends under the humid conditions of northeast India. *Agric Meteorology*, 149: 763–770.
- Mahida, H. R. and Patel, V. N., (2015) Impact of Climatological Parameters on Reference Crop Evapotranspiration using Multiple Linear Regression Analysis. *International Journal of Civil Engineering (IJCE)*. 2 (1): 21-24.
- Solomon, S., Qin, D., Manning, M. and Chen, Z., (2007) Climate change: the physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, IPCC Summary for policymakers.
- zone of Rajasthan (India). *Agric Water Manag.* 69: 1–11.
- Xu, C., Gong, L., Jiang, T., Chen, D. Singh, V. P. (2006) Analysis of spatial distribution and temporal trend of reference evapotranspiration and pan evaporation in Changjiang (Yangtze River) catchment.”, *J Hydrol.* 327: 81–93.

How to cite this article:

Yadvendra Pal Singh, H.K. Mittal, P.K. Singh, S.R. Bhakar and Jain, H.K. 2019. Impact of Metrological Parameters on Reference Evapotranspiration using Multiple Linear Regressions. *Int.J.Curr.Microbiol.App.Sci.* 8(07): 2122-2127.
doi: <https://doi.org/10.20546/ijemas.2019.807.255>