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Regression Analysis for Evaluation of Evopotranspiration for Agriculture Water Requirement

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Abstract

India Grapes Farming is very important sector of agriculture. Due to volatile weather condions and scare water resources irrigation management becomes challenging aspect for grapes farmers. The proposed system considers all challenges of Grapes Farming and developed automated irrigation system. The water resource management is the challanging task in agriculture. To Achieve water management in agriculture field many new technology has been proposed in recent research work, however very few work focused on productivity of crop while optimizing water resources. Proposed model considers all aspect of Irrigation like weather, crop growth stages and canopy coverage. Morever system also considers landscape information like slope of the farm area, soil type, elevation level etc.

Proposed system predicting most enflucing parameter for evaluation of Evopotranspiration(*ET0)* using Machine Learning Regression analysis Algorithm. *ET0* evaluation requires many parametrs like day Light hours, Vappour pressure, Longwave Radiation, Soil Heat Flux etc those are not readily available or one can not record it direcly. These parametrs are claculated using web scraped data then used in *ET0* evaluation process in addition to crop growth data and landscape information. This predictive model provides optimised parameter for evaluation of *ET0*. Proposed model showing very less error deviation in Actaul and precited values of *ET0*.

Keywords. Machine Learning, Regression Analysis, Agriculture water requirement, ET0 evaluation, algorithms, Irrigation, crop coefficient.

1. Introduction

IOT is one of the main hub among different technologies for connecting various heterogeneous things together. Now a days many distributed monitoring and control system using wireless sensor network to implement the applications for different areas. Presently many new system available in market that provids auto-irrigtaion, such system mostly configures based on fixed interval of irigation . In addition some system automatically start water pump when weatehr parameter crosses predefind threshold, some irrigtaion system starts automatically when soil moisture decreases. Population increasing day by day, so food requirement is also increasing. Fresh water feeding to agriculture increased tremendously because of high demand of food [1]. Most of the art of agriculture is irrigated through manual system without any controller and smart system. Smart automated system

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with microcontroller and sensor will provide better irrigation approach and such system has many advantages over manual system [2].

In proposed system last 10 years weather data is collected using python web scraping techniques. *ET0* evaluation [6] is carried out using scraped weather data. Architectural design includes number of slave nodes and one master node. Arduino nodes acting as slave node collect required weather parameter from different part of area as per different orientation. Mathematical methods are used to decide most influencing parameter in reference *ET0* evaluations. Finally water requirement is calculated and tuned with rain probability and soil moisture level using feed forward methods.

This paper focused on discussion of different smart irrigation methods and comparisons of different *ET0* evaluation methods for Multiple Linear Regression (MLR), experimentation and observation of *ET0* evaluation using proposed methodology based on first two parameters i.e. Maximum Temperature and Minimum Temperature is discussed in detail. In addition Multiple Linear Regression (MLR) using all parameters with ET0 is also discussed followed by optimization of parameters and conclusion.

2. Related Work

It's mandatory to optimize the use of freshwater for agriculture. Freshwater resources are decreasing day by day. Automation is very important in agriculture irrigation to optimize use of fresh water in irrigation [11]. Agriculture consuming 70% of fresh water for irrigation. In future, It becomes mandatory to find alternative source of water for agriculture [12]. Golstein et al.[14] proposed a recommendation based irrigation management system using the ML algorithm with the knowledge of the agronomist. Unplanned use of fresh water is most important factor in agriculture [15]. If any intelligent system is used for water management then economic growth [16] of country can be improved. Most of water used in irrigation is wasted due to runoff or percolation. Soil moisture is one important parameter in water requirement analysis [17], depend on evapotranspiration which can be calculated based on temperature and on extra-terrestrial radiation. Artificial intelligence algorithms composed of artificial neural network and fuzzy logic based methodology [19] is used to train real time weather data to predict soil moisture for irrigation scheduling. Weather parameters used for training are real-time air temperature, relative humidity, solar radiation, and wind speed.

In this study multiple regression analysis is used to find out water requirement for different soil types and in different climatic conditions. Some methods focused on detecting the water need of crop and time duration of motor to be ON [13]. Most of methods are based on Artificial Intelligence and fuzzy logic. Actual soil data collection is challenging task, to overcome that most of researcher train their models to predict soil moisture [19][20]. Some methods using ready dataset from previous literature instead of real time data. Proposed method using all weather, soil, crop, environmental parameters to evaluate total water and time of irrigation. It using Modern Machine learning algorithm for irrigation scheduling and Penman-Monteith method is used to calculate Evapotranspiration. This method giving best results with small error value among all methods available in literature. This method trying to optimize water as well as trying to reduce manual efforts in irrigation by reducing electricity requirement of agriculture. Evapotranspiration is very important factor in water requirement evaluation. This section focused on different methods used for calculation of evapotranspiration based on different criteria's. Table. 1 shows discussion and comparisons

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of different methods for Evapotranspiration Evaluation and parameters used in that evaluation. Based on availability of parameters proposed method finalize the ET0 evaluation method.

$$ETo = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_{2)}(e_s \ - e_{a)}}{\Delta + \gamma(1 + 0.34u_{2)}}$$

Table 1. Comparison of different Methods of Evapotranspiration Evaluation

Method Name	Evaluation	Parameter Used
Hargreaves and Somani	$)(Tmax - Tmin)^{0.5}$ $ET_0 = 0.0023R_a(T_{mean} + 17.8)(T_{max} - T_{min})^{0.5}$	Radiation and Mean Temperature
Ravazzanietal	$)(Tmax - Tmin)^{0.5}$ $ET_0 = (0.817 + 0.00022Z)0.0023R_a(T_{mean} + 17.8)(T_{max} - T_{min})^{0.5}$	Temperature
Thornthwaite equation	$ET_0 = 16 * \left(\frac{10T_i}{I}\right)^a \left(\frac{N}{12}\right) (\frac{1}{30})$ $)(Tmax - Tmin)^{0.5}$	Temperature, No. of Daylight hours
Solar radiation based method(Irmak, 2003)	$ET_0 = -611 + 0.149Rs + 0.07T_{mean}$	Temperature, Humidity, Radiation, No. of day light hours.
Net Radiation based method (Irmak 2003)	$ET_0 = 0.489 + 0.289Rn + 0.023T_{mean}$	Temperature, Humidity, Radiation, No. of day light hours.
The (FAO56) Penman-Monteith equation	$ETo = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_{2)}(e_s \ - e_{a)}}{\Delta + \gamma(1 + 0.34u_{2)}}$	Temperature, Humidity, wind speed, Radiation, Saturated vapor pressure

1. Hargreaves and Samani (1985) method is radiation based method used when some weather data is missing [8]. It is expressed as:

$$ET_0 = 0.0023R_a(T_{mean} + 17.8)(T_{max} - T_{min})^{0.5} \qquad (1)$$

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Here Ra is extraterrestrial radiation, Tmean is mean daily temperature, Tmin is daily minimum temperature and Tmax is daily max temperature.

2. Ravazzanietal(2012) method. Hargreaves equation is an alternative to penman equation when all required weather data is not available.
Ravazzanietal method [8] is used when only temperature data is available. In this method, the Hargreaves coefficient is adjusted based on local elevation.

$$ET_0 = (0.817 + 0.00022Z)0.0023R_a(T_{mean} + 17.8)(T_{max} - T_{min})^{0.5} \quad (2)$$

3. Thornthwaite method:

$$ET_0 = 16 * \left(\frac{10T_i}{I}\right)^a \left(\frac{N}{12}\right) \left(\frac{1}{30}\right) ET0 = 16 * \left(\frac{10Ti}{I}\right)^a \left(\frac{N}{12}\right)\left(\frac{1}{30}\right)$$

(3)

Where Ti is the mean monthly temperature [°C], N is the mean monthly sunshine hour. This method generally gives overestimate in a humid area and underestimate in the arid area [9].

4. Solar radiation-based method (Irmak, 2003)

$$ET_0 = -611 + 0.149Rs + 0.07T_{mean} \quad (4)$$

Here R_s is solar shortwave Radiation and Tmean is average of Min and max temperature [10].

5. Net Radiation based method (Irmak, 2003)

$$ET_0 = 0.489 + 0.289Rn + 0.023T_{mean} \quad (5)$$

Here R_n is Net radiation and Tmean is average of Tmax and Tmin[10].

6. Penman (1948) combination method

$$ETo = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2)(e_s - e_a)}{\Delta + \gamma(1+0.34u_2)} \quad (6)$$

By using the FAO Penman-Monteith equation for *ET0,* It is easy to calculate crop coefficients at research sites by relating *Kc = ETc/ET0*. Penman method giving best results to calculate water requirements.

As shown in Table 2. Minimum error generated after applying multiple regression by MaxTemp parameter. R-Square is used to find closeness of regression line to data. It is also called coefficient of multiple determination. Higher the R –squared value better the model fits your data.

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3. Proposed System Model

Proposed model is developed in two phases. First phase is data acquisition with the help of web scraping techniques and Wunderground API. Daily collected weather data and site specific information is used to calculate the evapotranspiration rate Goldstein et al.[14] of the crop at different growth stages that is main factor in water requirement of crop. Using data science techniques, cleaning and preprocessing of scrapped data is performed to avoid difficulty in later stage of evaluation. Processed Data is converted into MySQL Database for application of Machine Learning Algorithms. Most of parameters required for evaluation of *ET0* like solar shortwave Radiation, Net radiation, No. of day light hours are not available readily to log directly into system. Evaluation and calculations of all these parameters is done using Python3 programming language based on collected data. Proposed method also calculates co-linearity between all independent parameters so the parameters those are strongly co-linear can be skip from further calculations.

In agriculture water requirement of any crop is depend on Evapotranspiration (*ET0*). Many environmental factors like day light hours, dew point, humidity, slope of the landscape, crop growth stages are required to evaluate *ET0*. In proposed model *ET0* is evaluated using Penman-Monteith equation.

$$ET0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_{2)}(e_s - e_{a)}}{\Delta + \gamma(1 + 0.34u_{2)}} \tag{7}$$

Dataset used in this method is split into two parts. 80% of data is split as training data and 20% of data as testing data. The machine learning model is trained using training data and is tested using testing data to make an optimized decision. Equation B is used for evaluating regression between *ET0* and one independent variable at a time. It's a Regression analysis model, here a is intercept, b is coeficient and X is the indepndent variable. Y is Dependent variable.

$$Y=a + bX + £ \tag{8}$$

The proposed method considering total 13 parameters, so when number of parameters are more than one then Multiple Regression Analysis (MLR) come into practice. MLR is used here to do predictive analysis and find out optimized results from numerous parameters. Equation C is used for evaluation of Multiple Linear Regression.

$$Y=\beta 0+\beta 1xi1+\beta 2xi2+...+\beta pxip+\epsilon \tag{9}$$

Here, i=n observations, Y= dependent variable xi= independent variable $\beta 0$=y-intercept βp=slope coefficients for each independent variable ϵ=residual.

a. *Algorithm*

- Finalization of weather data parameters.
- Analysis of different web scraping techniques.
- Web scrapping of weather data using python Beautiful Soup.

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- Application of different data cleaning and preprocessing techniques on scrapped weather data.
- Creation and configuration of webserver using XAMMP control panel and conversion of csv file into database.
- Evaluation of all required parameter like day light hours, Net radiation etc. using weather data.
- Evaluation of different *ET0* methods and implementation of *ET0* using Penman-Monteith method, pupation of database with *ET0* dependent variable.
- Implementation of Simple Linear Regression method in python for each independent parameter with dependent variable (*ET0*).
- Implementation of Multiple Linear Regression method in python using all independent parameters with dependent variable *(ET0).*
- Optimization of independent parameter using r squared error, p value and root mean square value.

b. Experimentation

Experimentation setup is installed in Aurangabad city in 15X15 feet area.

Plantation done in that area to avoid pesticides and other dieses of plants. In one row 10 plants are planted. Actually this research especially for grapes farming but practically it was impossible to install setup on grapes frames. Grape farming having specific period for each stage of plant growth, it's not possible to adjust that period with prototype installation time. Proposed method assumed that there is no or little multi- linearity in values of all parameters. In addition method also assumed that all observations are independent of each other and variance is same for all values of independent variable. If in latter stage face any problem of co-linearity then scatter plots can be used to solve that problem.

Grapes farming Period assumed from October to February. It's assumed that in month of October, there is no any canopy coverage. After period of 45 days there is 50% canopy coverage. After 90 days whole area of grapes farm is covered by canopy of grapes plant. This assumptions are helpful at the time of initial setup of prototype. Figure 1. Shows some records of dataset. It contains the parameters Maximum Temperature, Minimum Temperature, Average Temperature, Maximum Humidity, Minimum Humidity, Average Humidity, Maximum Dew point, Minimum Dew point etc.

```
The first few lines of our dataset looks like this:
------------------------------------------------
       Date  Max_TempF  Max_Temp  ...  Pre_max  Pre_min      ET0
0  1/1/2012          0        27  ...    29.95    29.80  5.01219
1  1/2/2012         86        30  ...    29.95    29.80  4.56783
2  1/3/2012         87        31  ...    29.95    29.83  5.30937
3  1/4/2012         84        29  ...    29.95    29.83  4.36538
4  1/5/2012         87        31  ...    29.98    29.86  4.92184

[5 rows x 22 columns]
```

Figure 1. Sample data of weather dataset

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Figure 2. Shows statistical analysis of the dataset. Statistical information contains mean value std. value min value and max value and percentage values of each parameter. E.g. Mean value of max temperature is 32.45 it's calculated using python library.

```
Statistical Details of the Dataset
-----------------------------------------------
        Max_TempF     Max_Temp  ...     Pre_min          ET0
count  2464.000000  2464.000000  ...  2464.00000  2464.000000
mean     89.700893    32.494724  ...    29.73390     5.557134
std       4.709186     2.439019  ...     0.10299     1.092610
min       0.000000    24.000000  ...    29.39000     2.687030
25%      87.000000    31.000000  ...    29.65000     4.865298
50%      90.000000    33.000000  ...    29.74000     5.515820
75%      93.000000    34.000000  ...    29.80000     6.142530
max     105.000000    41.000000  ...    30.01000    20.600900

[8 rows x 21 columns]
```

Figure 2. Statistical analysis of weather dataset

Figure 3. Linear Regression Analysis is performed using ET0 as dependent variable (DV) and Minimum Temperature as Independent variable (IV). In this result 5.54 is the intercept (constant) of DV and 0.2435 is the coefficient. If value of IV changes by one unit DV will change by 0.243.

```
Calculated Intercept  and Coefficient using Multiple Linear Regression:
-------------------------------------------------
Intercept:  5.548865459739995
Coefficient:  [0.24357428]
```

Figure 3. Simple Linear Regression using Minimum Temperature and *ET0*

Proposed method evaluated regression analysis with two different methods to validate the intercept and coefficient. As shown in Figure 4. Constant and coefficient(x1) value is same as calculated in previous method-squared value is 0.056 and p value is less than 0.05.

```
State Model:
-------------------------------------------------
Statemodel :                            OLS Regression Results
==============================================================================
Dep. Variable:                    ET0   R-squared:                       0.056
Model:                            OLS   Adj. R-squared:                  0.056
Method:                 Least Squares   F-statistic:                     117.6
Date:                Tue, 30 Mar 2021   Prob (F-statistic):           1.20e-26
Time:                        02:44:04   Log-Likelihood:                -2780.9
No. Observations:                1971   AIC:                             5566.
Df Residuals:                    1969   BIC:                             5577.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          5.5489      0.022    248.202      0.000       5.505       5.593
x1             0.2436      0.022     10.843      0.000       0.200       0.288
==============================================================================
Omnibus:                      759.354   Durbin-Watson:                   2.028
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             7559.725
Skew:                           1.525   Prob(JB):                         0.00
Kurtosis:                      12.097   Cond. No.                         1.01
==============================================================================
```

Figure 4. OLS Regression Model

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Figure 5. Shows some rows of actual and predicted values of *ET0*, as *ET0* is Dependent variable (DV) in proposed system, Machine Learning model is applied to predict ET0 values based on training data.

```
Actual and predicated values of ET0:
-------------------------------------------------
      Actual   Predicted
2167  3.48387   5.230171
2369  6.14188   5.817943
2441  5.61778   5.622019
511   6.93849   5.883251
148   6.88733   5.883251
...       ...        ...
1883  8.31182   5.230171
2064  4.02695   5.622019
2105  7.25152   5.752635
837   5.71969   5.622019
8     5.00505   5.230171

[493 rows x 2 columns]
```

Figure 5. Actual and predicted *ET0*

Figure 6. Shows plots that plotted with actual and predicted values of *ET0* on y axis and number of observations on y axis. As per plot actual and predicted values are very close except some observation nearby 30th observation.

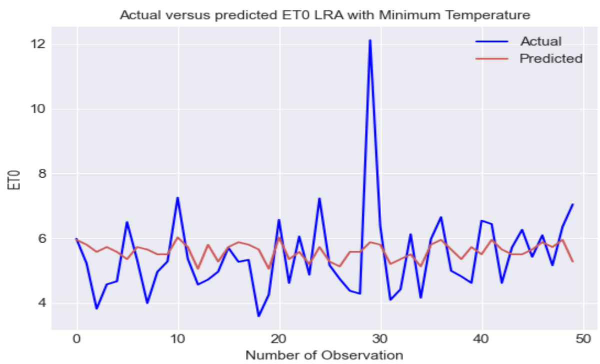

Figure 6. Plot for Actual and predicted ET0

Figure 7. Shows Scatter plot of *ET0* versus Minimum temperature. Scatter plot showing good relationship between Independent variable and Dependent variable. Training dataset is used for plotting of this scatter plot. Figure 8. Shows Scatter plot of *ET0* versus Minimum temperature by using testing dataset. As per scatter plots both training and testing dataset showing good relationship with Dependent variable (*ET0*)

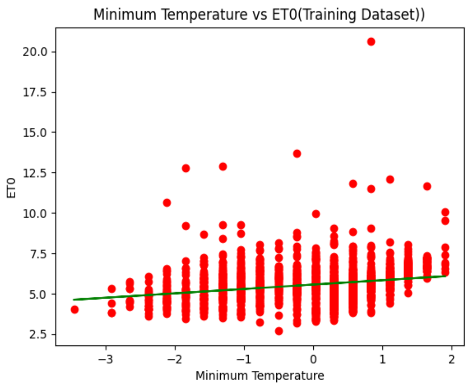

Figure 7. Scatter plot of *ET0* versus Minimum Temperature using training dataset

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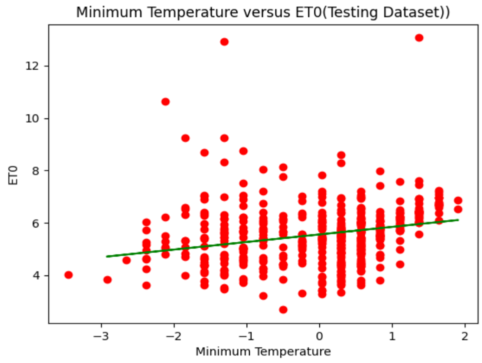

Figure. 8 Scatter plot of *ET0* versus Min. Temperature using testing dataset

Figure 9. Shows Linear Regression Analysis using *ET0* as dependent variable (DV) and Maximum Temperature as Independent variable. In this result 5.5587 is the intercept (constant) of DV and 0.2796 is the coefficient. If value of IV changes by one unit DV will change by 0.2796.

```
Calculated Intercept  and Coefficient using Multiple Linear Regression:
--------------------------------------------------
Intercept:  5.5587891188661835
Coefficient:  [0.2796351]
```

Figure 9. Linear Regression Analysis using *ET0* and Maximum Temperature

Proposed method evaluated regression analysis with two different methods to validate the intercept and coefficient. Figure 10. Shows OLS Regression Results. In OLS method calculated Constant and Coefficient(x1) values are exactly same as calculated in previous regression method. Squared value is 0.068 and p value is less than 0.05. Results using this parameter (Maximum Temperature) showing very good relation with dependent variable (*ET0*).

```
Statemodel :                            OLS Regression Results
==============================================================================
Dep. Variable:                    ET0   R-squared:                       0.068
Model:                            OLS   Adj. R-squared:                  0.067
Method:                 Least Squares   F-statistic:                     142.8
Date:                Tue, 30 Mar 2021   Prob (F-statistic):           8.05e-32
Time:                        03:23:05   Log-Likelihood:                -2887.7
No. Observations:                1971   AIC:                             5779.
Df Residuals:                    1969   BIC:                             5791.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          5.5588      0.024    235.531      0.000       5.513       5.605
x1             0.2796      0.023     11.949      0.000       0.234       0.326
==============================================================================
Omnibus:                     1312.693   Durbin-Watson:                   1.974
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            56230.125
Skew:                           2.553   Prob(JB):                         0.00
Kurtosis:                      28.664   Cond. No.                         1.01
==============================================================================
```

Figure 10. OLS Regression Model

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Figure 11. Shows some results that contains actual and predicted values of *ET0*. Proposed system using Machine learning algorithm to predict *ET0*. Model is trained using training dataset and testing dataset is used for prediction.

```
Actual and predicated values of ET0:
-----------------------------------------------------
      Actual   Predicted
895   5.97689  5.942680
245   5.21865  5.792726
923   3.80930  5.567796
2065  4.56385  5.717750
1740  4.65730  5.567796
...       ...       ...
720   4.08546  5.117935
611   5.81503  5.867703
1031  6.44317  5.567796
2211  5.93694  5.117935
613   5.68218  5.867703

[493 rows x 2 columns]
```

Figure 11. Actual and predicted *ET0*

Figure 12. Shows plots of actual and predicted values of *ET0* on y axis and number of observations on x axis. There is very less error deviation in actual and predicted values of *ET0* when Maximum Temperature is used as independent parameter.

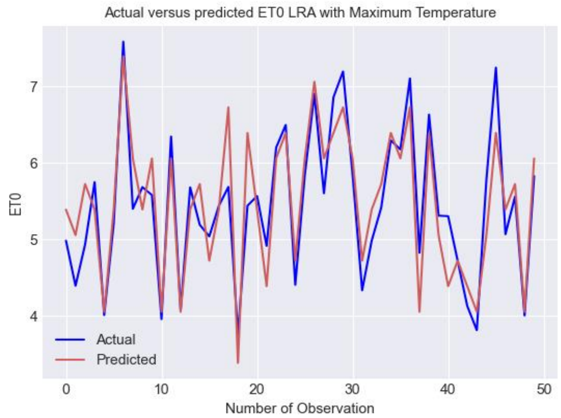

Figure 12. Plot for Actual and predicted ET0

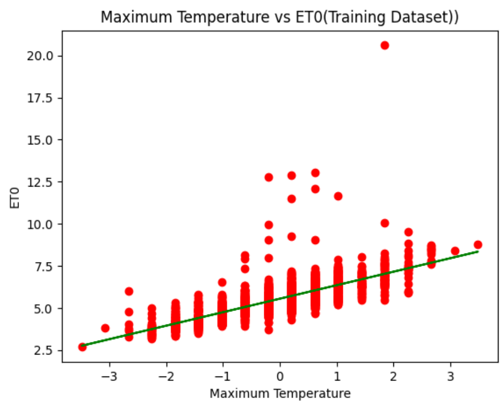

Figure 13. Scatter plot of *ET0* versus Maximum Temperature using training dataset

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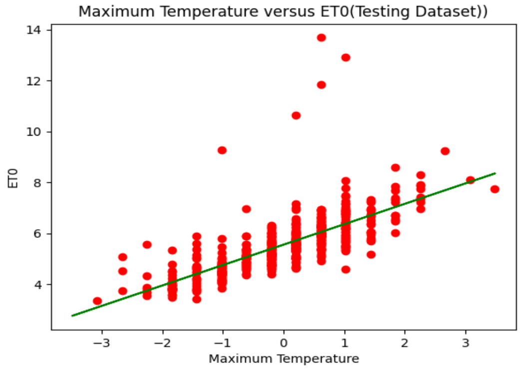

Figure 14. Scatter plot of *ET0* versus Maximum Temperature using testing data

Below section focused on multiple independent parameters to evaluate relationship between all independent parameters and dependent parameter. Figure 15. Shows regression coefficient for all independent variables.

```
Calculated Coefficient of all Indpendent variables using Multiple Linear Regression:
-------------------------------------------------
           Coefficient
Max_Temp      0.621117
Min_Temp      0.604236
Avg_Temp      0.040177
rh_max       -0.189754
rh_min       -0.500256
rh_avg        0.059528
Dew_max      -0.261614
Dew_avg       0.591912
Dew_min      -0.453240
Wind_max      0.568969
Wind_min      0.049928
```

Figure 15. MLR using all Independent Variables.

Figure 16. Shows OLS regression model, 5.5601 is intercept (constant) of regression and x1 - x11 are coefficients of regressions for all independent parameters. Fig. 16 and Fig. 17 showing exactly same results for coefficients of independent variables, it validates proposed model of regression.

```
State Model:
-------------------------------------------------
Statemodel :                            OLS Regression Results
==============================================================================
Dep. Variable:                    ET0   R-squared:                       0.928
Model:                            OLS   Adj. R-squared:                  0.928
Method:                 Least Squares   F-statistic:                     2310.
Date:                Thu, 08 Apr 2021   Prob (F-statistic):               0.00
Time:                        13:41:54   Log-Likelihood:                -368.13
No. Observations:                1971   AIC:                             760.3
Df Residuals:                    1959   BIC:                             827.3
Df Model:                          11
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          5.5601      0.007    843.061      0.000       5.547       5.573
x1             0.6211      0.023     27.384      0.000       0.577       0.666
x2             0.6042      0.035     17.115      0.000       0.535       0.673
x3             0.0402      0.039      1.024      0.306      -0.037       0.117
x4            -0.1898      0.024     -7.932      0.000      -0.237      -0.143
x5            -0.5003      0.033    -15.169      0.000      -0.565      -0.436
x6             0.0595      0.045      1.329      0.184      -0.028       0.147
x7            -0.2616      0.133     -1.963      0.050      -0.523      -0.000
x8             0.5919      0.362      1.634      0.102      -0.118       1.302
x9            -0.4532      0.256     -1.769      0.077      -0.956       0.049
x10            0.5690      0.007     80.222      0.000       0.555       0.583
x11            0.0499      0.007      6.977      0.000       0.036       0.064
==============================================================================
Omnibus:                     1303.858   Durbin-Watson:                   2.036
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           344200.251
Skew:                          -1.979   Prob(JB):                         0.00
Kurtosis:                      67.618   Cond. No.                         176.
==============================================================================
```

Figure 16. OLS Regression Model

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Figure 17. Shows some of the records of actual and predicted *ET0* values, here training dataset is used to train the machine learning model and testing dataset is used to test the model. Fig. 18 is showing plot of actual and predicted *ET0* on y axis and number of observations on x axis.

```
Actual and predicated values of ET0:
-------------------------------------------------
       Actual  Predicted
1622  6.68458   6.737683
295   6.14195   6.502852
872   6.20038   6.125382
2021  4.96604   5.121724
1636  4.82912   4.822724
...       ...        ...
2436  5.01021   5.073332
2253  5.22792   5.701626
1084  5.19275   5.615200
1726  3.83760   3.936309
1797  6.52140   6.525572

[493 rows x 2 columns]
```

Figure 17. Actual and predicted *ET0*

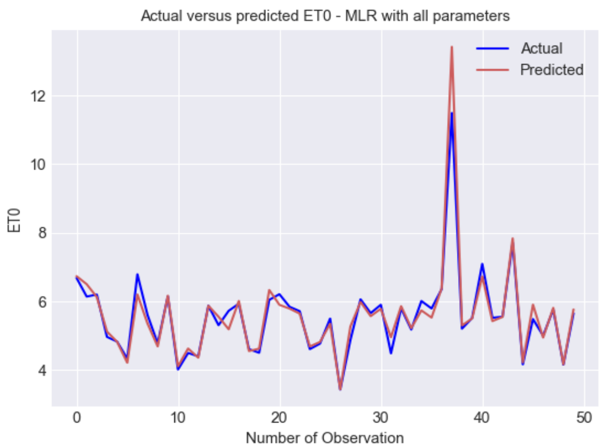

Figure 18. Plot for Actual and predicted ET0

Figure 19. Shows Mean absolute error, mean squared error and root mean squared error. Here root mean squared error is 0.250057 which is less than 10% of mean value of dataset. This is very good indication in regression analysis.

```
Mean Absolute Error , Mean Squared Error and Root Mean Squared Error
-------------------------------------------------
Mean Absolute Error: 0.17400289119400875
Mean Squared Error: 0.06252860335552965
Root Mean Squared Error : 0.250057200167341
```

Figure 19. Mean Absolute Error, Mean Squared Error & Root Mean Squared Error

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Table 2. Shows Errors, R2 and p values generated by Maximum Temperature and Minimum Temperature parameter. Maximum Temperature parameter showing minimum error in multiple linear Regression. R-Square is used to find closeness of regression line to data. It is also called coefficient of multiple determination. Higher the R –squared value better the model fits your data. As shown in Table 2. Max Temp is significantly related to *ET0*. No any other parameter satisfying conditions of linearity with *ET0*.

Table 2. Parameter Optimization

	Error	**F**	**R2**	**P**
Min Temp/ET0	1.2866	117	0.056	0
Max Temp/ET0	1.0953	142	0.068	0
Multiple Linear Regression(MLR)	0.2500	2310	0.928	0

4. Conclusion and Future Discussion

Proposed method is Smart Irrigation method that manages crop water requirement by analyzing and predicting many environmental and crop specific factors those are critical parameters in water requirement analysis. In addition proposed method also considering crop growth stage, canopy coverage, sea elevation level for analysis of water requirement. Most of the available methods used temperature and soil moisture parameters to calculate water requirement of crop. The parameters considered in proposed method are day light hours, Net Radiation, Long Wave Radiation, Temperature, Humidity, Soil Heat Flux, crop coefficient, crop canopy, sea elevation level of landscape, air temperature, wind speed, soil temperature, having very high contribution in evapotranspiration, and ET0 is very important parameters to calculate water requirement of crop. Proposed method consider each and every factor that is important for water requirement evaluation, Machine Learning model performs better than other model by giving very low error deviation between predicted values and actual values. In proposed method prediction is done using two different methods of machine learning to increase the accuracy of system. Root Mean Square Error given by Multiple Linear Regression is 0.2500, which is very good indication of accuracy of the model to predict the values. Proposed method provides low cost prototype model with 92% of accuracy in observed results.

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