Study of ET_0 by using Conventional and Soft Computing Techniques in the Eastern Gandak Project in Bihar, India – A Case Study

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7th Meeting of the WG-IDM,
8th October 2022, Adelaide, Australia

INTRODUCTION

- The population of India is rapidly growing at a compound rate of 2.3 % per annum.
- The country has no option but to attempt to feed its rapidly expanding population through large scale development of major, medium and minor irrigation schemes.
- Agriculture sustainability needs viable options like supplemental irrigation to meet the crop water requires as when it's needed.
- Proper estimation of ET_0 provides very useful information for irrigation water management.

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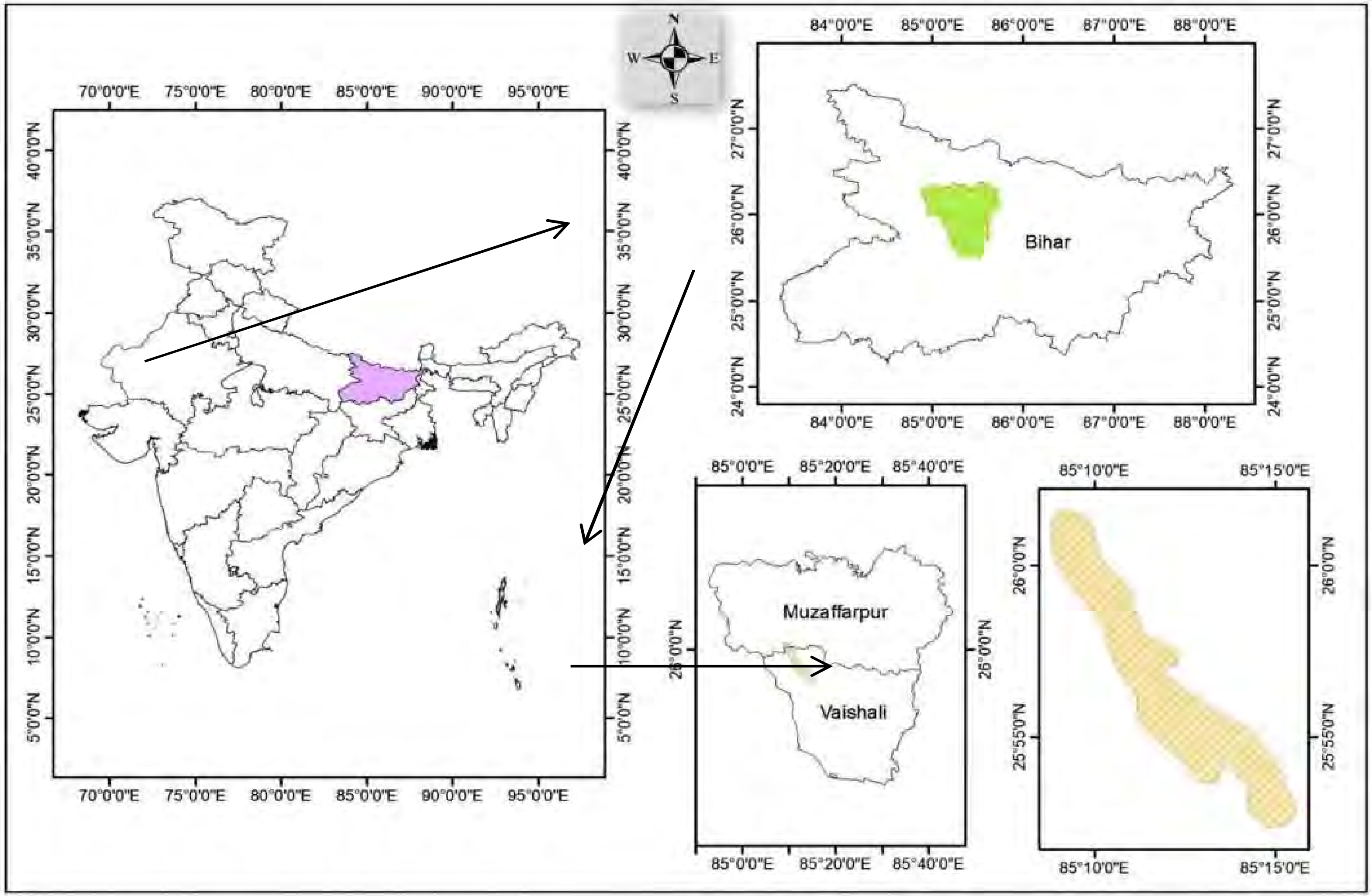
- Different conventional methods have been proposed by the researchers, over time, to estimate the ET_0 from different climatic parameters.
- Based on the various weather data availability, the FAO24(1977) advised using four methods: Pan Evaporation Method, Radiation Method, Blaney-Criddle Method, and Modified Penman Method.
- But, due to rigorous local calibrations these methods show limited global accuracy.
- To resolve this problem, FAO-56(1998) advised that reference evapotranspiration be calculated using Penman-Monteith Method.
- On the other hand, soft computing methods are considered as intelligent alternatives to the above methods due to the ease of application and saving time.

STUDY AREA

- Bhagwanpur Distributary is the tail end distributary of the Eastern Gandak Project which takes off from the Vaishali Branch Canal.
- The command area lies in Muzaffarpur and Vaishali districts of the Indian state of Bihar between longitude 85°7’30” E and 85°15’0” E and latitude 25°52’30” N and 26°3’0”N.
- The Bhagwanpur distributary’s command area is covered by Saraiya block in Muzaffarpur district and Vaishali block in Vaishali district.
- The Bhagwanpur Distributary has a gross command area of 2250 hectares and a total cultivable command area of 1841 hectares.



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85°20'0"E
85°40'0"E
26°0'0"N
Muzaffarpur
Vaishali
85°10'0"E
85°15'0"E
26°0'0"N
25°55'0"N

METHODOLOGY

- Reference evapotranspiration (ET_0) has been determined by conventional methods i.e., Modified Penman method, Hargreaves method, Pan Evaporation method and Penman-Monteith method for the data of Pusa.
- ET_0 has been estimated using three different soft computing techniques i.e., SVM, GPR and ANN.
- 75% data has been used for the training of the soft computing models while the 25% data has been used for the testing.

Estimation of ET_0 Using Conventional Methods

Blanney Criddle Method

- This method is suggested for areas, where available climatic data cover air temperature data only. The relationship recommended, representing mean value over the given month is expressed as:

$$ET_0 = c * P (0.46 T + 8) \text{ mm/day} \quad (1)$$

Where,

ET_0 = Reference crop evapotranspiration in mm/day for the month considered,

T = Mean daily temperature in °C over the month considered,

P = Mean daily percentage of total annual day time hours obtained from the relevant table for a given month and latitude

c = Adjustment factor, which depends on minimum relative humidity, sunshine hours and daytime wind estimates.

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- This method is useful where only temperature data in precise form is available and the other parameters can be available in general terms. The method has the following limitations
- Blaney - Criddle method is not suitable in equatorial regions where temperature remains fairly constant but other weather parameters change.
- Not suitable for small islands, where air temperature is affected by surrounding sea temperature, showing little response to seasonal change in radiation.
- High altitude, where daytime radiation is practically independent of night temperature.
- Climate with a high variability in sunshine hours during transition month.

Radiation Method

- This method is suggested for areas where available climatic data include measured air temperature and sunshine, cloudiness or radiation, but not measured wind and humidity. Knowledge of general levels of humidity and wind is required. and these are to be estimated using published weather descriptions, extrapolation from nearby areas or from local sources.
- Relationships are given between the presented radiation formula and reference crop evapotranspiration (ET_0). taking into account general levels of mean humidity and daytime wind. The relationship recommended is expressed as:

$$ET0 = c * (W.R_s) \tag{2}$$

Where,

ET_0 = Reference crop evapotranspiration in mm/day for the month considered

R_s = Solar radiation in equivalent evaporation in mm/day

W = Weighting factor, which depends on temperature and altitude

c = Adjustment factor, which depends on temperature and altitude

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- The Radiation method should be more reliable than the Blaney-Criddle method.
- In fact, in equatorial zones, on small islands, or at high altitudes, the Radiation method may be more reliable, even if measured sunshine or cloudiness data are not available, in this case solar radiation maps prepared for most locations in the world should provide the necessary solar radiation data.
- Except for equatorial zones, climatic conditions for each month or shorter period vary from year to year, and consequently ET_0 varies (FAO-24, 1977).
- This method is simple in application and can be conveniently used where radiation is the dominating factor in evapotranspiration.
- It can be used near equatorial regions. in coastal areas, in small islands or in high altitude regions. It is somewhat inaccurate in places in the interior regions, especially if the places are at low altitudes.

Modified Penman Method

The FAO-24(1977) recommended this method as the best method for the estimation of ET_0 but later it was observed that this method overestimates. The relationship recommended is expressed as,

$$ET_0 = c \times [W \times R_n + (1 - w) \times f(u) \times (e_a - e_d)] \quad (3)$$

Where,

ET_0 = Reference crop evapotranspiration in mm/day

W = Temperature related weighting factor

Rn = Net radiation in equivalent evaporation in mm/day

f(u) = wind related function

$(e_a - e_d)$ = difference between the saturation vapour pressure at mean air temperature and the mean actual vapour pressure of the air, both in mbar,

c = Adjustment factor to compensate for the effect of day and night weather conditions

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- The suggested wind function applies to conditions found during summer, with moderate winds, relative humidity of about 70 percent and day-night wind ratios of 1.5 to 2.0. No adjustment is required for these conditions.
- However, if 24-hour wind totals are used there will be an under-prediction of ET_0 by 15 to 30 percent in areas where daytime wind greatly exceeds nighttime wind, where RH_{max} approaches 100 percent, and where radiation is high.
- Conversely, for areas experiencing moderate to strong wind, where night time humidity (RH_{max}) is low, and where radiation is low, the equation will over predict ET_0, this over-prediction increases with decreasing ratios of U_{day}/U_{night}. Under these conditions an adjustment factor (c) should be applied.
- The modified Penman method would offer the best results with minimum possible error of plus or minus 10 percent in summer, and up to 20 percent under low evaporative conditions (WALMI, 1988).

Hargreaves Method

Apart from the latitude data, this method requires temperature data. At least, for interior regions with simple topography and frost-free growing seasons, the equation claims to be superior to many other formulas.

The equation used to calculate ET_0 is given by,

$$ET_0 = 0.0023 \times R_a(T + 17.8) \times TD^{0.5} \quad (4)$$

Where,

ET_0 = Reference crop evapotranspiration in mm/day

R_a = Extra-terrestrial radiation (mm/day)

T = Mean temperature (^{0}C),

TD = Difference in maximum and minimum temperature (^{0}C)

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- The equation is comparatively very simple and requires only the temperature data apart from the latitude.
- The equation claims to be superior to many other equations at least for interior locations with plain topography where the growing seasons of the crops are frost free.

Pan Evaporation Method

- ET_0 can be estimated using the pan evaporation data using the following relation.

$$ET_0 = K_p \times E_{pan} \quad (5)$$

Where,

K_p = Pan coefficient, and

E_{pan} = Pan evaporation (mm/day)

- The pan method can be graded next to modified Penman method with possible error of 15 percent, depending on the location of the pan (WALM1,1988).

Penman Monteith Method

The FAO 56 recommended the use of this method for the estimation of reference The relationship recommended is expressed as,

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{(T+273)} \times U_2(e_s - e_a)}{\Delta + \gamma(1+0.34U_2)} \quad (6)$$

Where,

ET_0 = Reference Evapotranspiration (mm/day), T = Air temperature (^{0}C), ɤ = Psychometric constant (kPa^{0}C^{-1}), G = Soil heat flux density (MJ/m^2/day), U_2 = Wind speed at 2m height (m/s), R_n = Net radiation at the crop surface (MJ/m^{2}day), (e_s– e_a) = Vapour pressure deficit (kPa), e_a = Actual vapour pressure (kPa), e_s = Saturation vapour pressure (kPa), Δ = Slope vapour pressure curve (kpa^{0}C^{-1}), and 900 is a conversion factor.

Support Vector Machine

- SVM is a supervised machine learning technique for regression and classification based on the statistical learning theory proposed by Vapnik (1999).

- SVM projects the input features into high dimensional space using kernels, resulting in sparse representation and robust decision making.

- MATLAB has been used to develop the SVM regression models using Linear epsilon-insensitive SVM (ε-SVM) regression.

Gaussian Process Regression

- Gaussian process regression is a powerful, non-parametric kernel-based probabilistic tool for regression in high dimensional space.
- The advantage of GPR is its ability to provide uncertainty estimations and to learn the noise and smoothness parameters from training data.
- MATLAB is used to develop the GPR regression models. Using different kernel functions i.e., Rotational Quadratic, Squared Exponential, Matern 5/2 and Exponential and best is selected based on the performance.

Artificial Neural Network

- An Artificial Neural Network is based on the structure and functions of biological neural networks.
- It is a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.
- Levenberg-Marquardt training algorithm with 10 hidden layers has been used.

- Four different cases of input data set to the soft computing models have been considered.

Case	Inputs	Output
1	T_{max}, T_{min}, RH_{max}, RH_{min}, Wind Speed, Sunshine Hours	ET_0
2	T_{max}, T_{min}, RH_{max}, RH_{min}, Wind Speed	ET_0
3	T_{max}, T_{min}, RH_{max}, RH_{min}	ET_0
4	T_{max}, T_{min}	ET_0

RESULTS AND DISCUSSION

Comparisons of Results of ET_0

Year	Month	Hargreaves Method	Pan Evaporation Method	Modified Penman Method	FAO 56 Penman Monteith Method
2016	January	2.65	0.7	1.71	1.31
2016	February	3.84	1.67	2.62	1.95
2016	March	5.21	2.85	3.88	3.12
2016	April	7.02	5.34	5.32	4.07
2016	May	5.82	4.1	4.78	4.56
2016	June	5.84	3.54	4.68	4.51
2016	July	4.38	2.3	3.47	3.4
2016	August	4.7	2.84	4.28	4.27
2016	September	3.95	2.05	2.99	2.96
2016	October	3.95	2.01	3.36	2.88
2016	November	3.69	1.49	2.51	2.01
2016	December	2.16	0.57	1.41	1.44

RESULTS AND DISCUSSION

Performance in Training				
Method	Coefficient of Determination (R^2)			
	Case 1	Case 2	Case 3	Case 4
SVM	0.98	0.96	0.93	0.91
GPR	**0.99**	**0.99**	**0.97**	**0.95**
ANN	0.98	0.96	0.91	0.92

Performance in Testing				
Method	Coefficient of Determination (R^2)			
	Case 1	Case 2	Case 3	Case 4
SVM	0.97	0.92	0.95	0.93
GPR	0.97	0.92	0.94	0.94
ANN	**0.98**	**0.96**	**0.95**	**0.95**

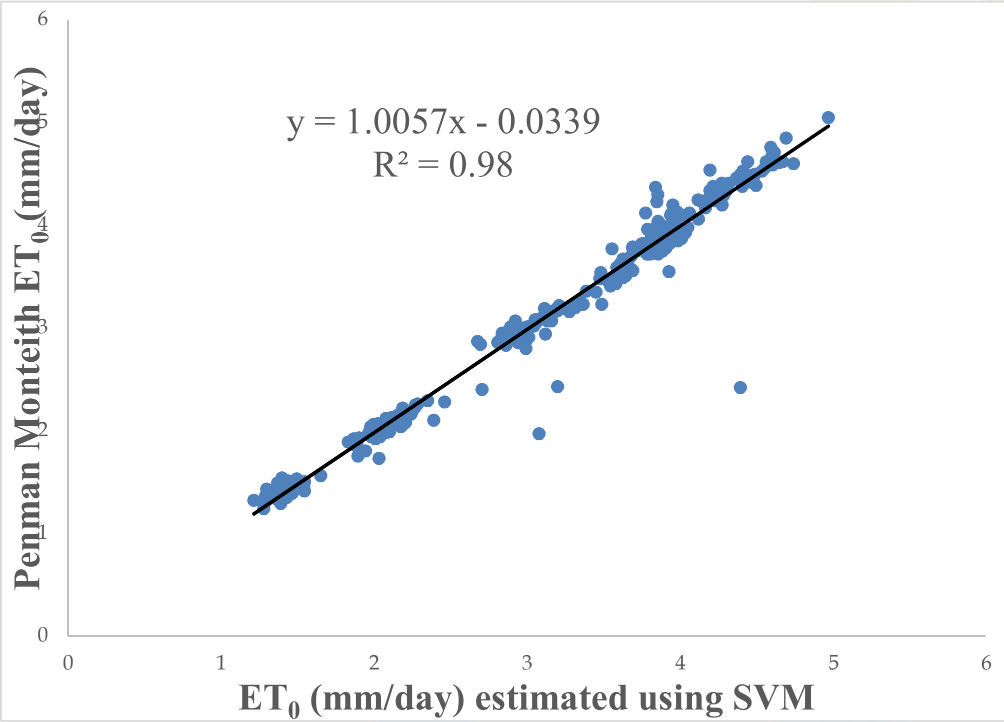


Fig 1. Performance of SVM in Training for Case 1

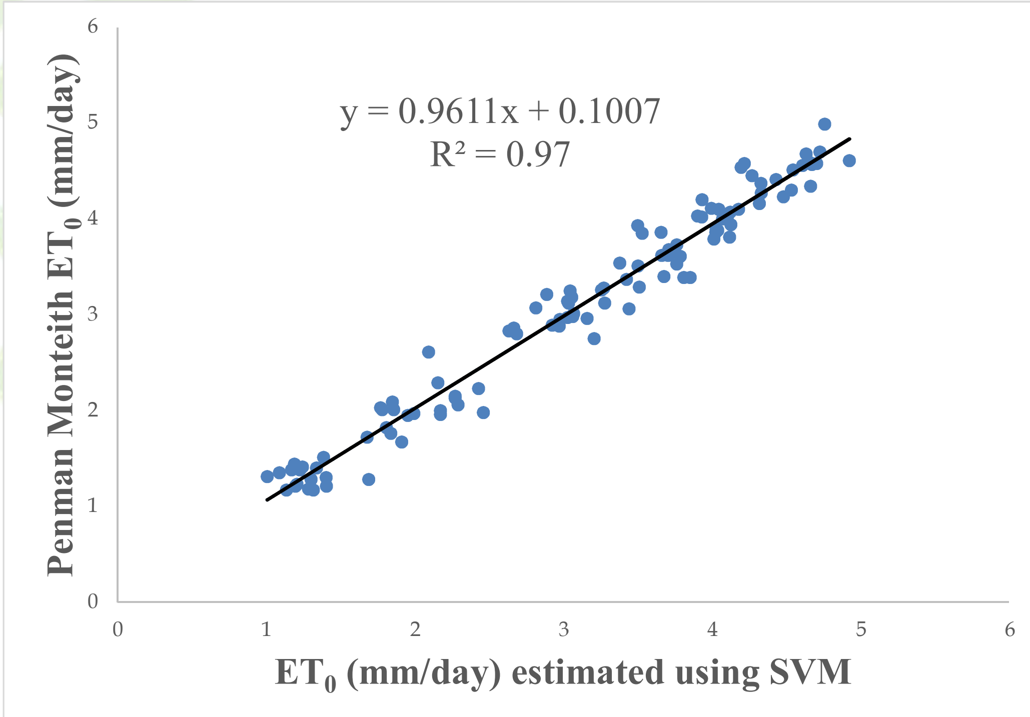


Fig 2. Performance of SVM in Testing for Case 1

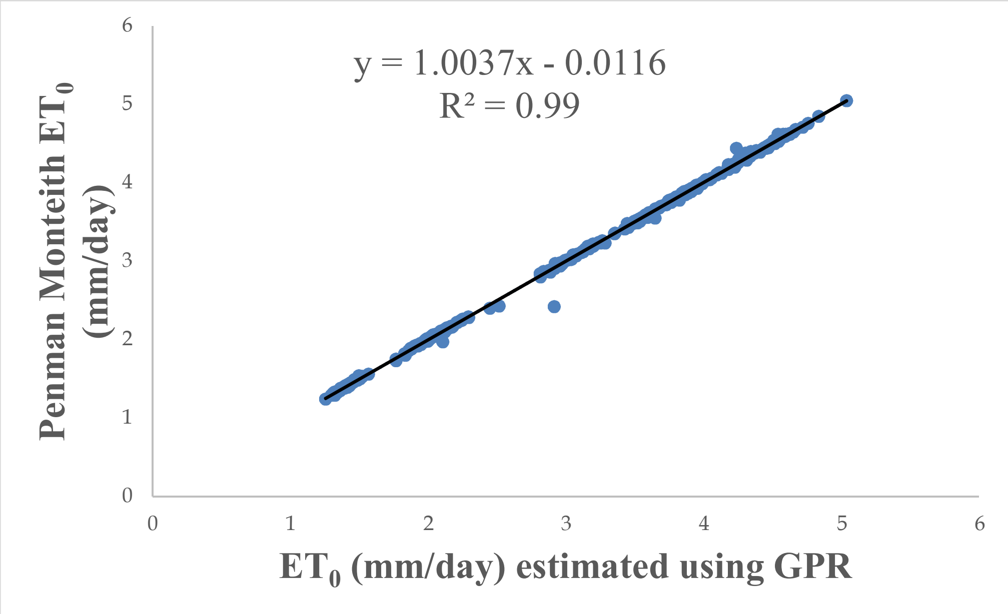


Fig 3. Performance of GPR in Training for Case 1

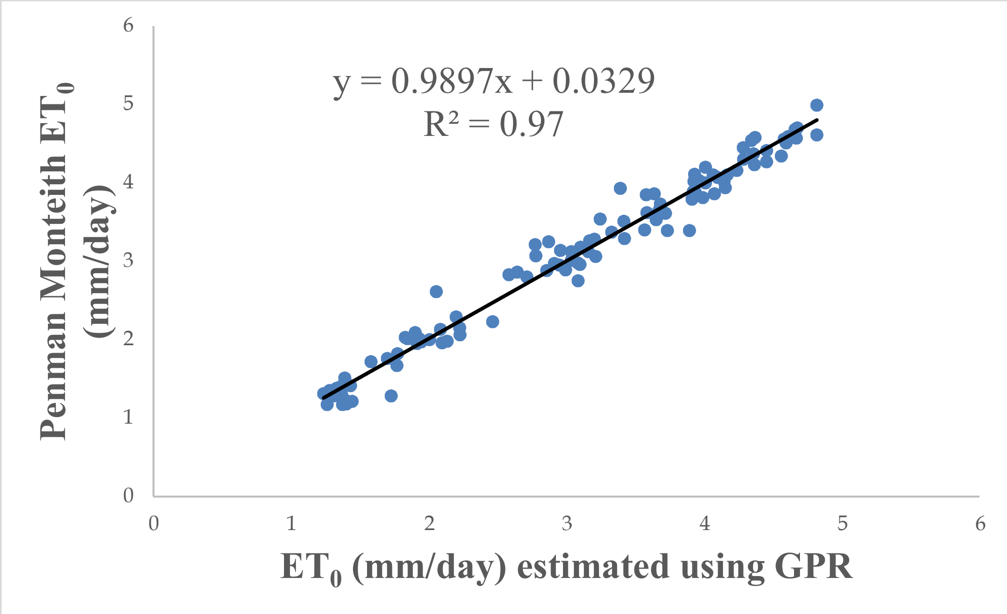


Fig 4. Performance of GPR in Testing for Case 1

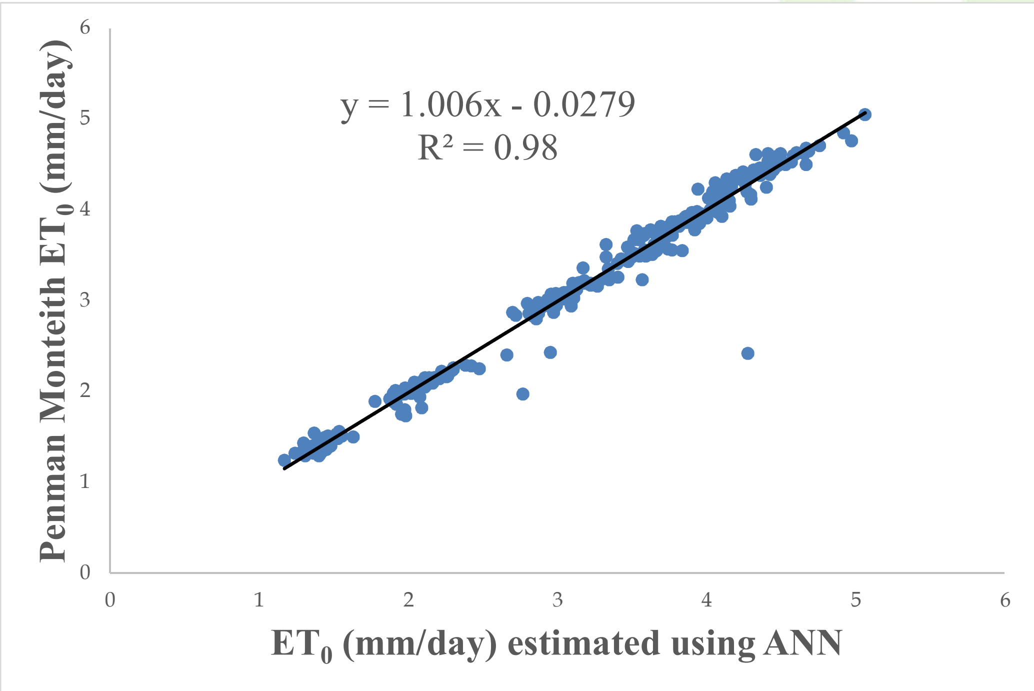


Fig 5. Performance of ANN in Training for Case 1

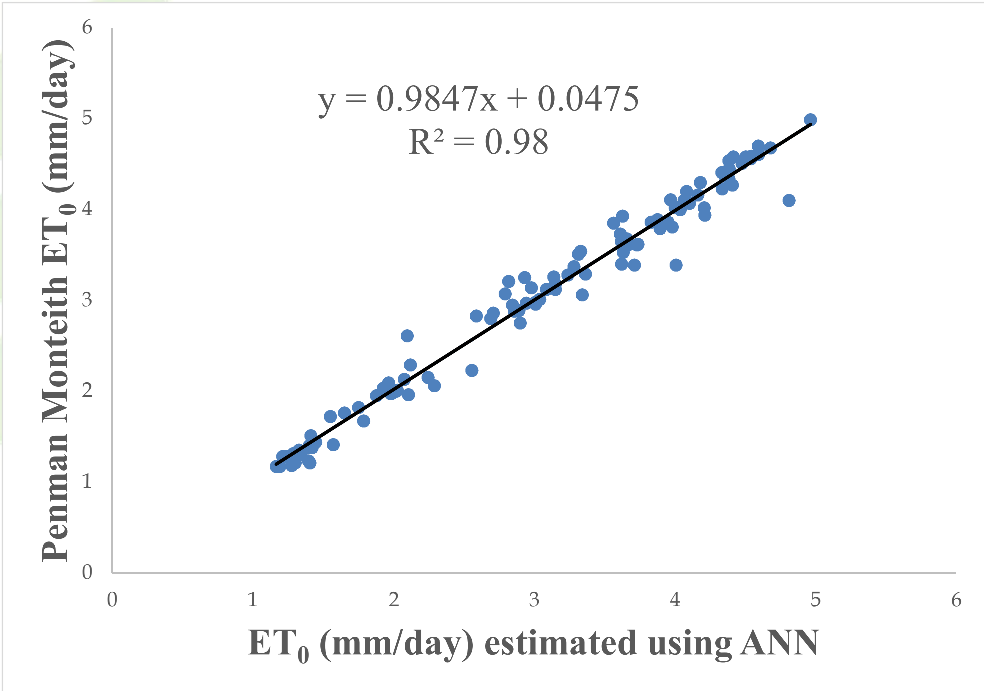


Fig 6. Performance of ANN in Testing for Case 1

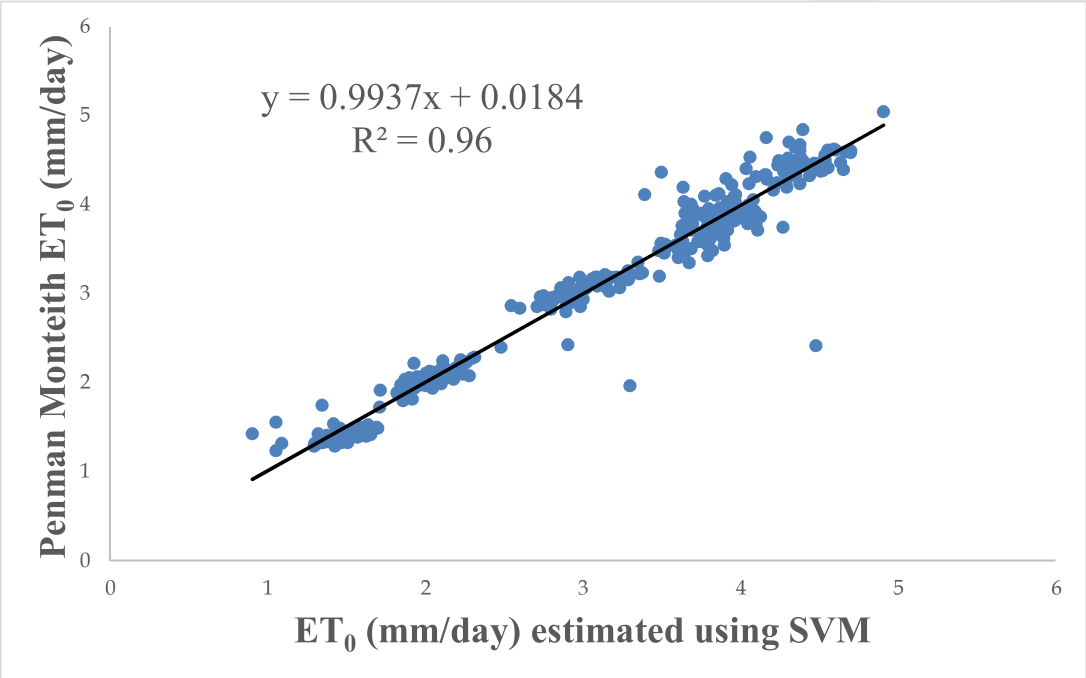


Fig 7. Performance of SVM in Training for Case 2

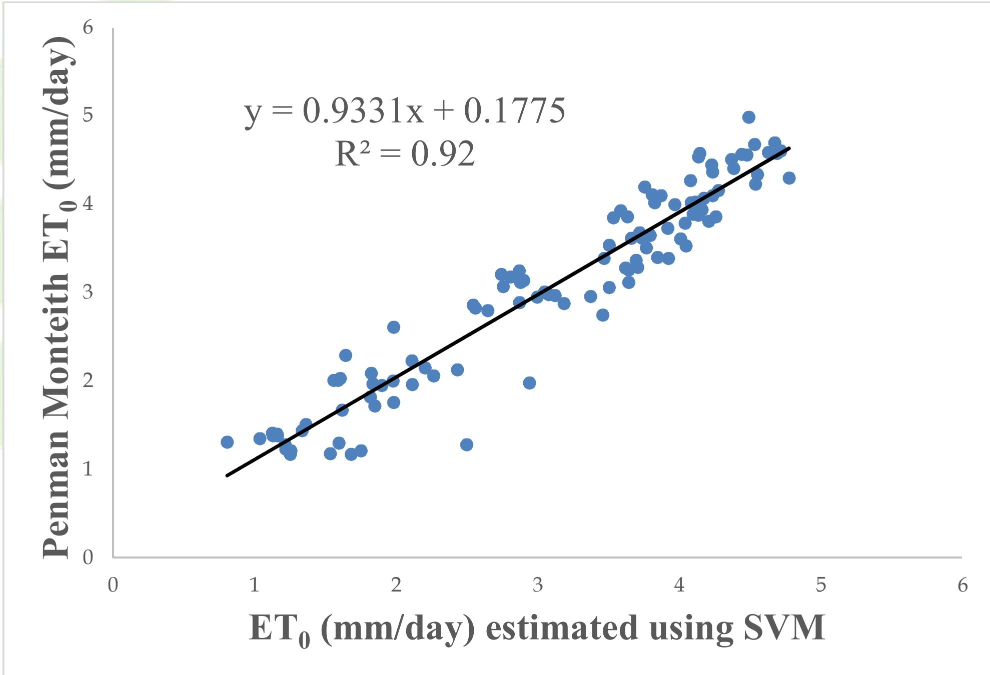


Fig 8. Performance of SVM in Testing for Case 2

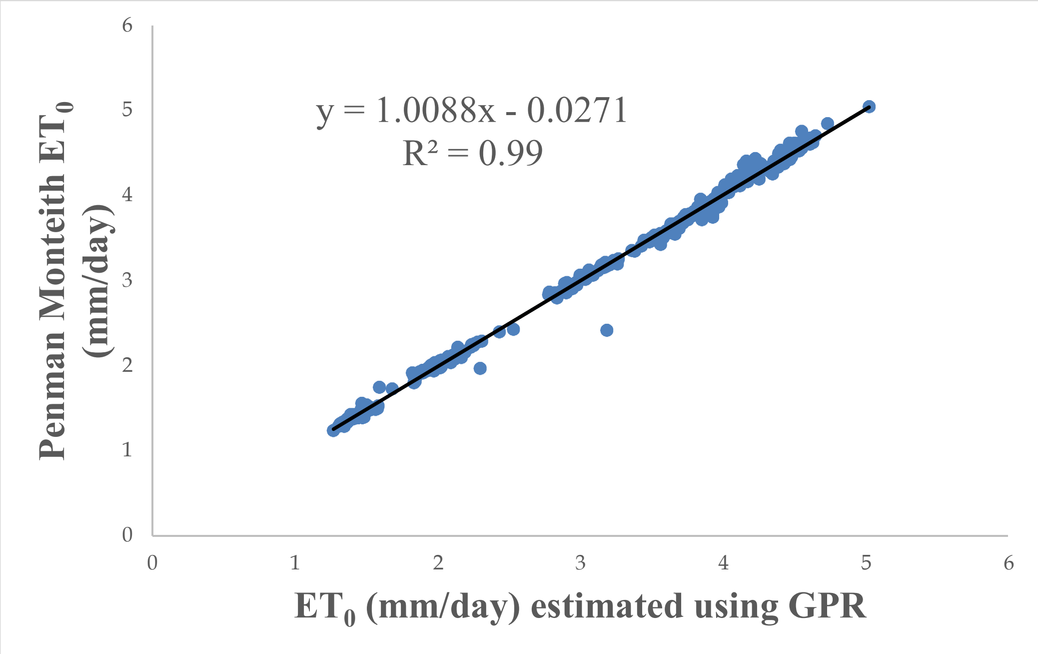


Fig 9. Performance of GPR in Training for Case 2

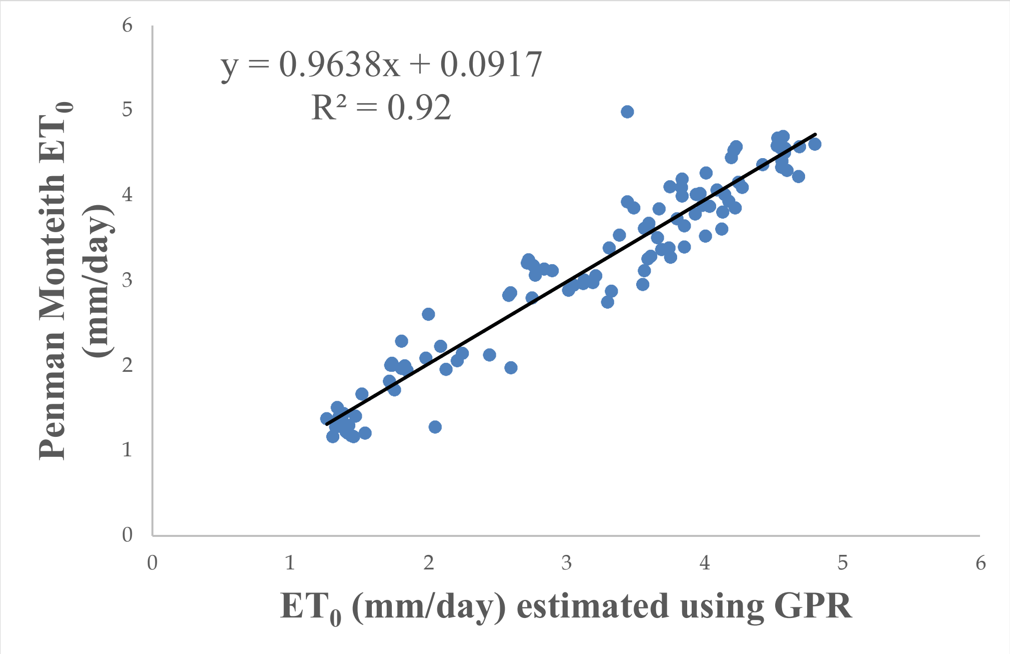


Fig 10. Performance of GPR in Testing for Case 2

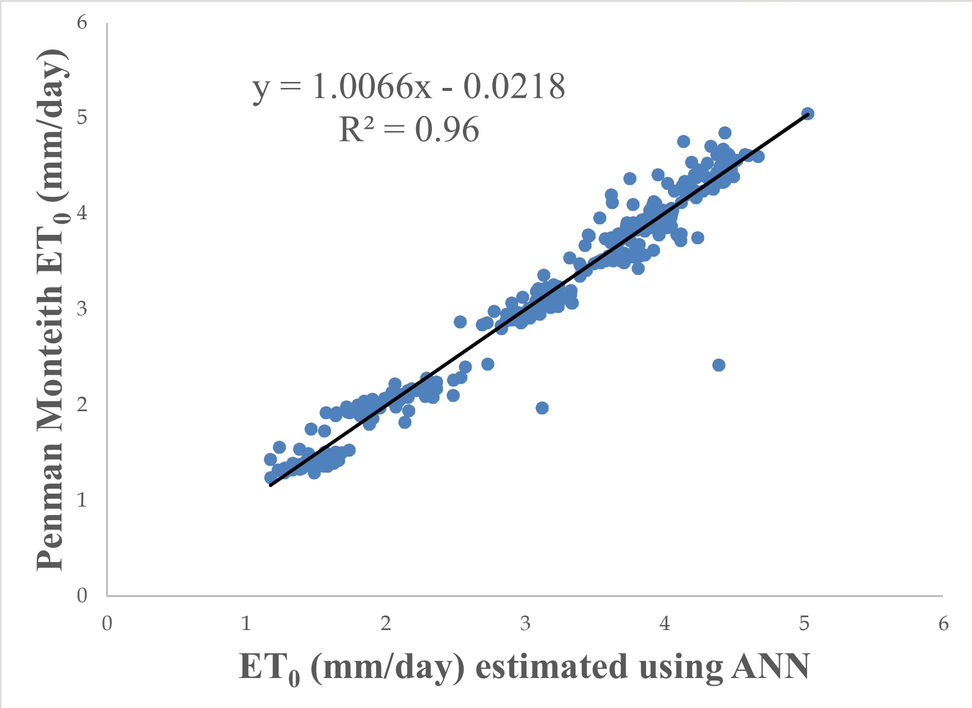


Fig 11. Performance of ANN in Training for Case 2

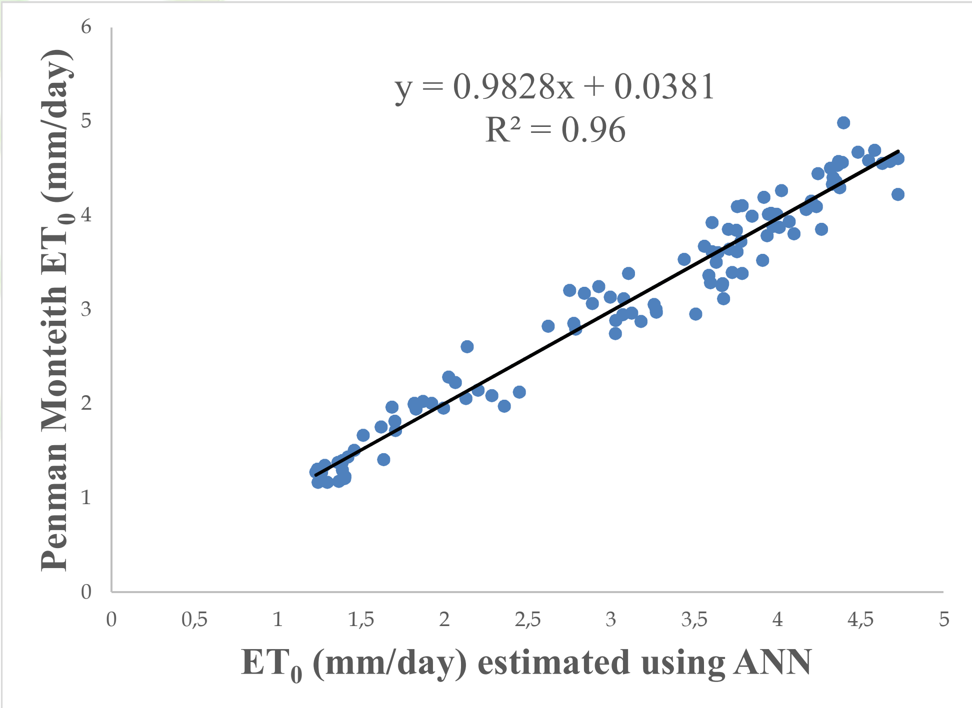


Fig 12. Performance of ANN in Testing for Case 2

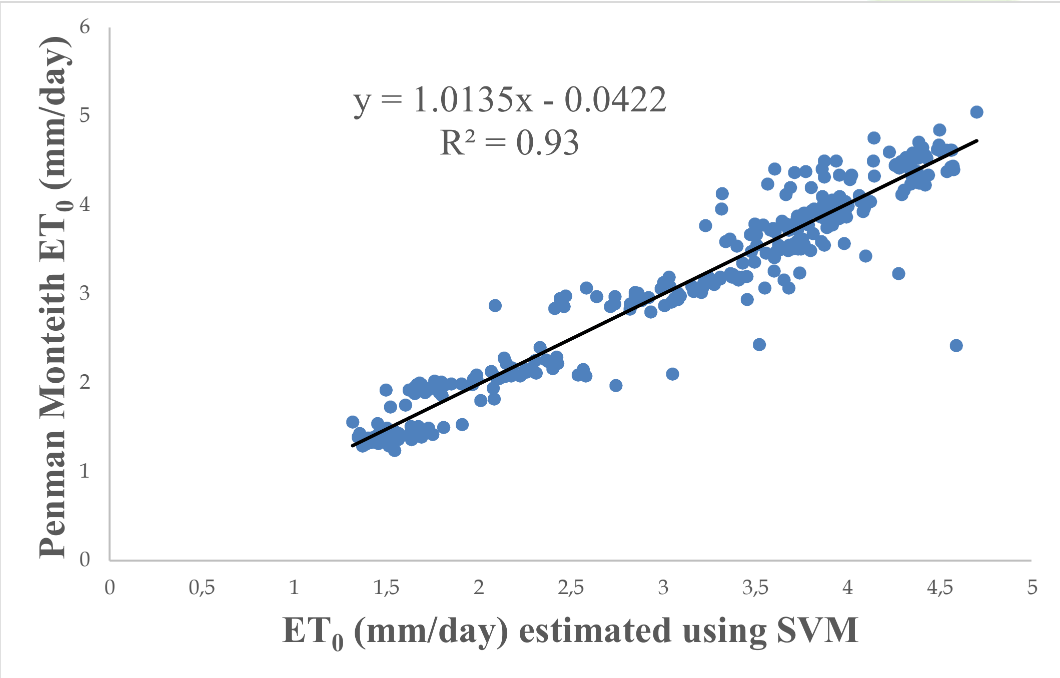


Fig 13. Performance of SVM in Training for Case 3

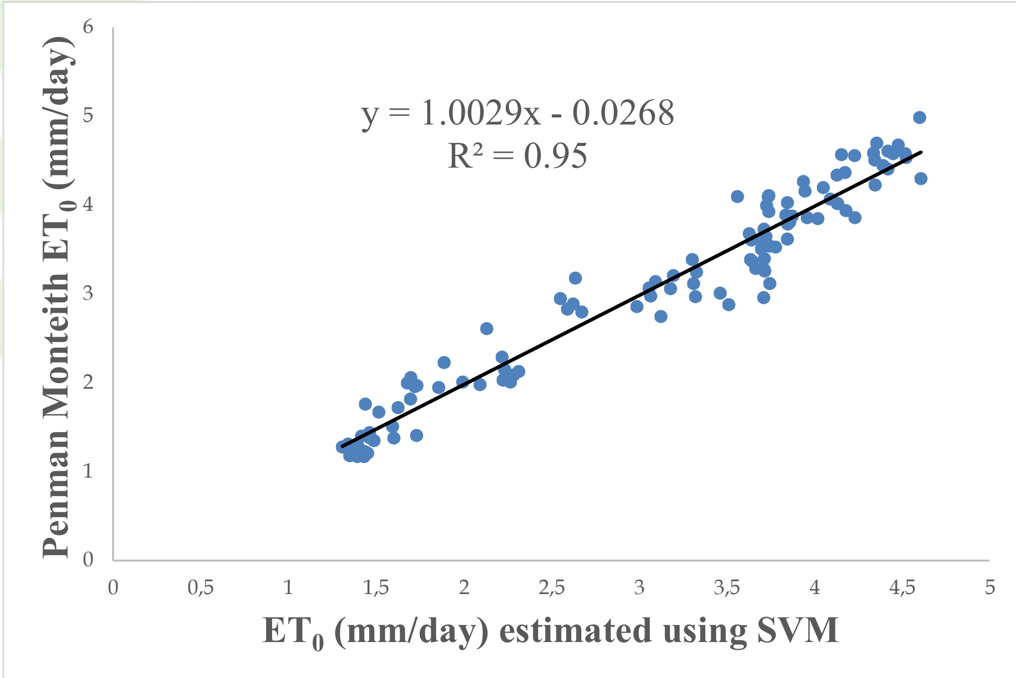
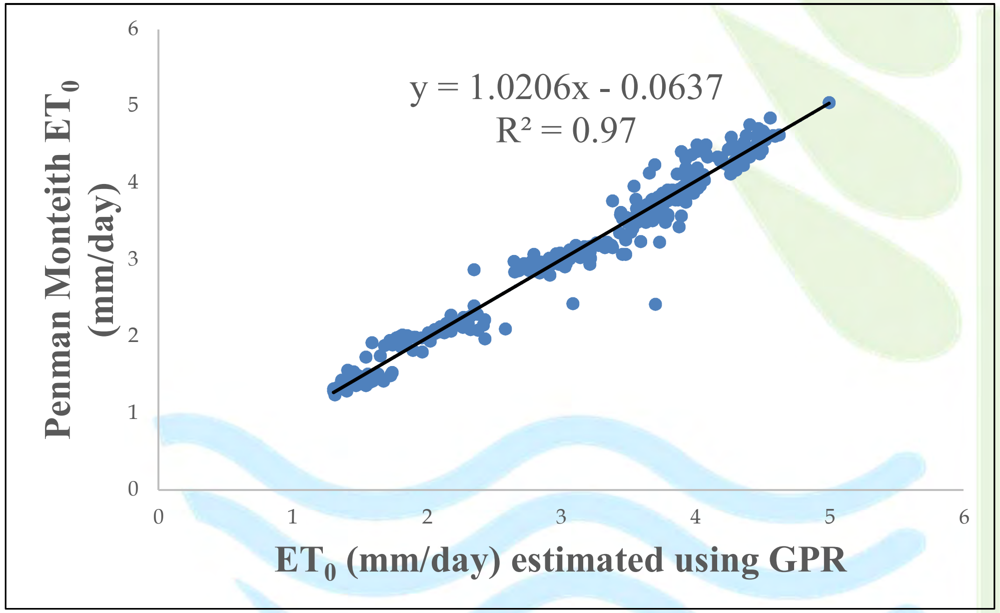


Fig 14. Performance of SVM in Testing for Case 3



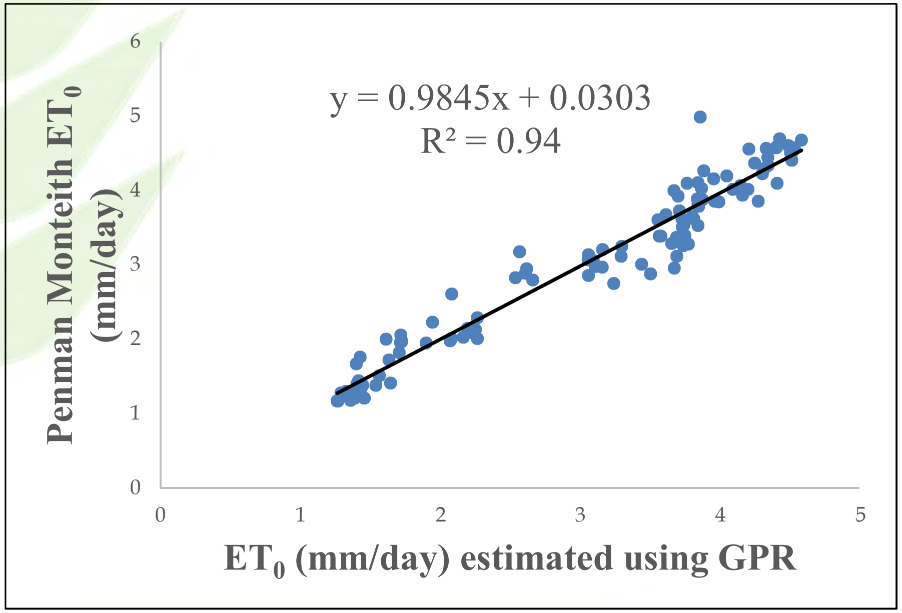


Fig 15. Performance of GPR in Training for Case 3

Fig 16. Performance of GPR in Testing for Case 3

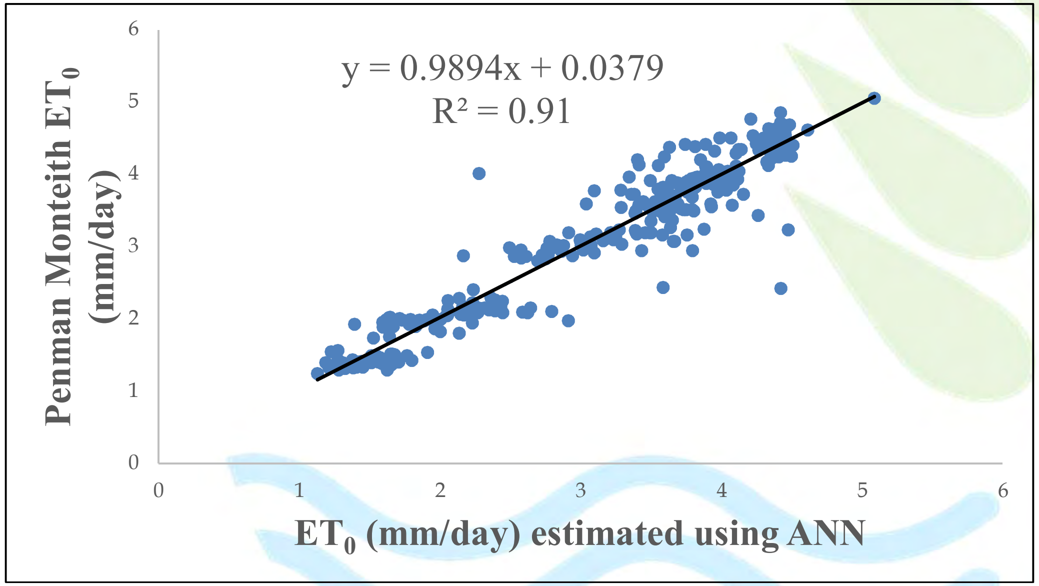


Fig 17. Performance of ANN in Training for Case 3

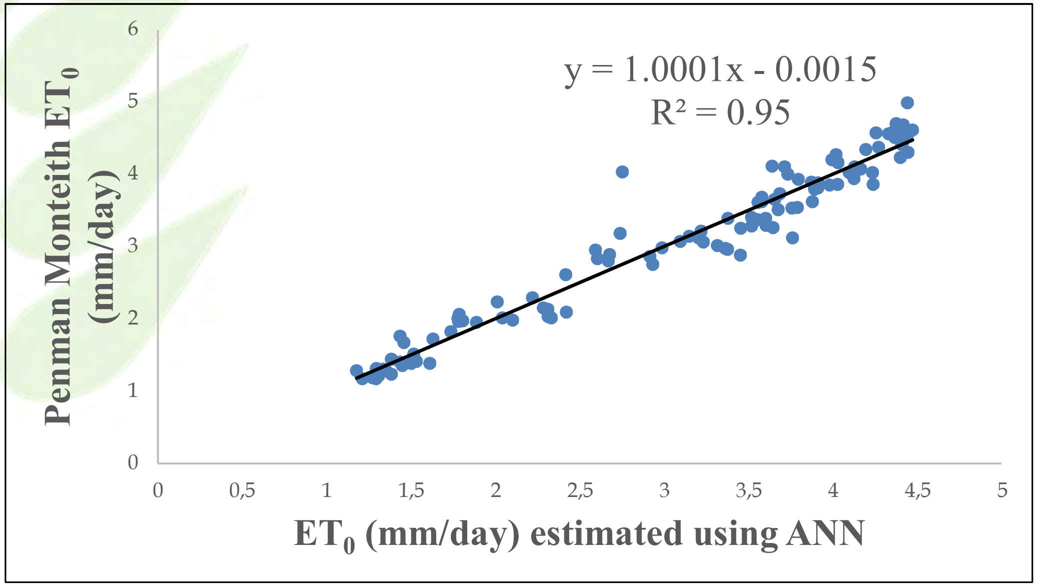


Fig 18. Performance of ANN in Testing for Case 3

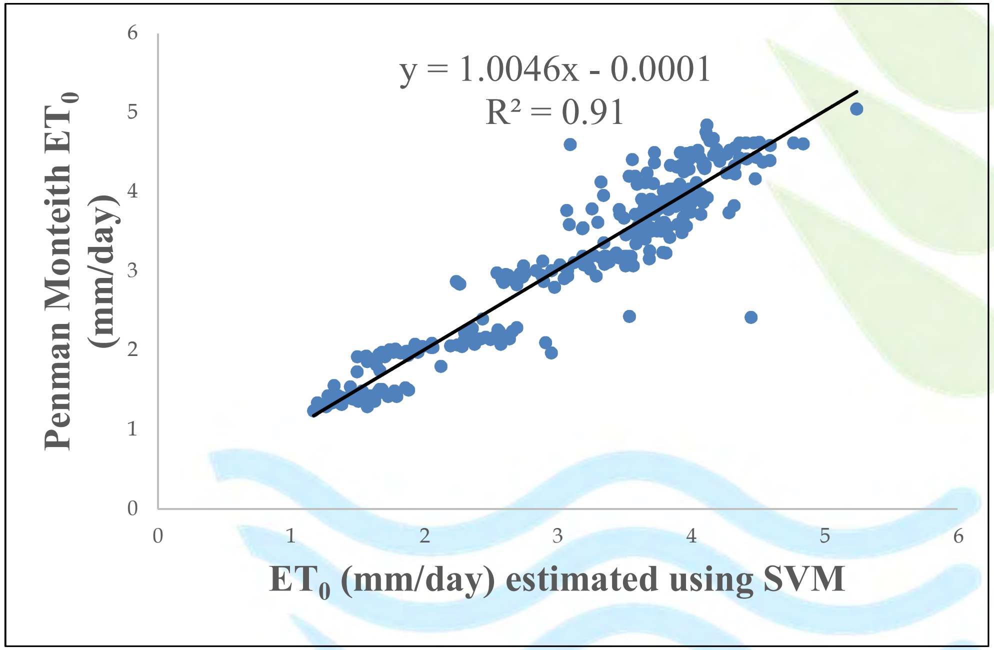


Fig 19. Performance of SVM in Training for Case 4

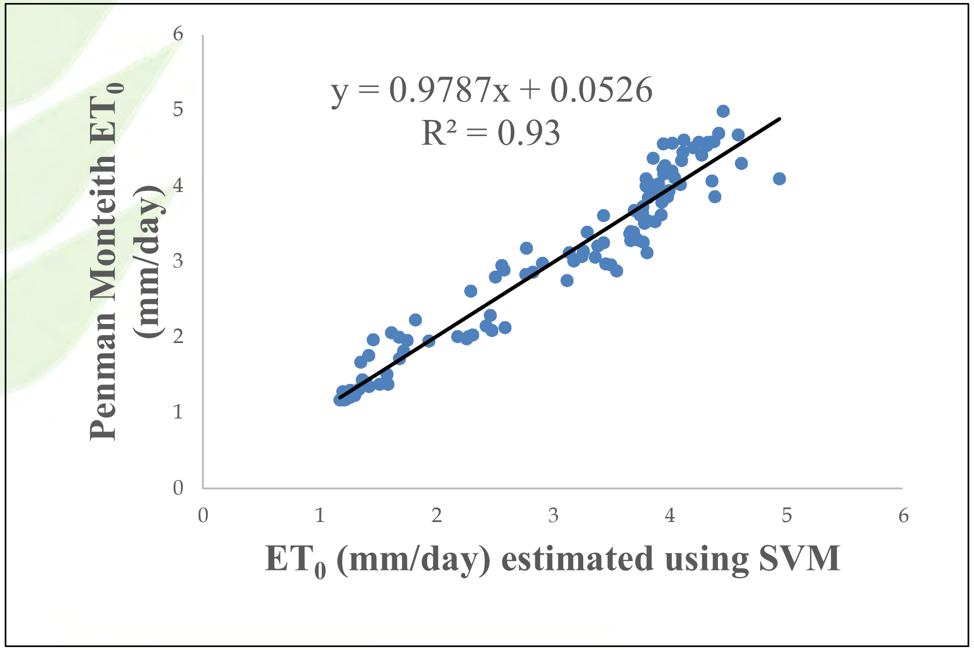


Fig 20. Performance of SVM in Testing for Case 4

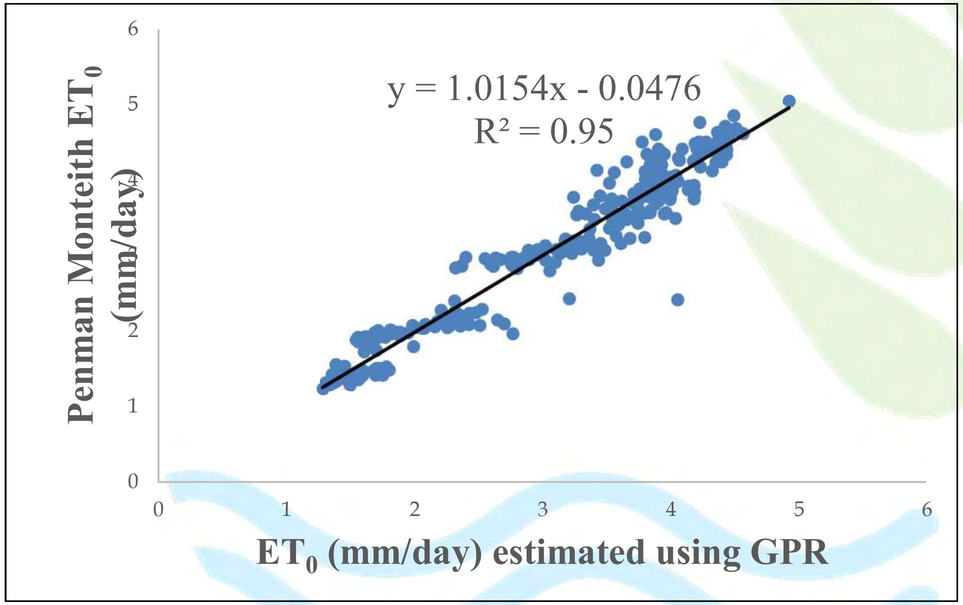


Fig 21. Performance of GPR in Training for Case 4

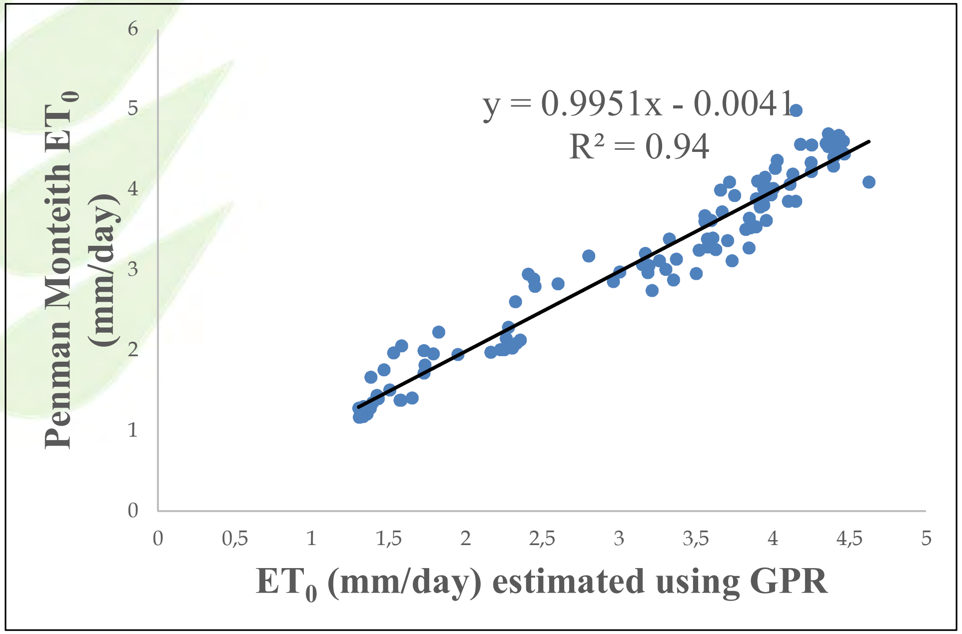


Fig 22. Performance of GPR in Testing for Case 4

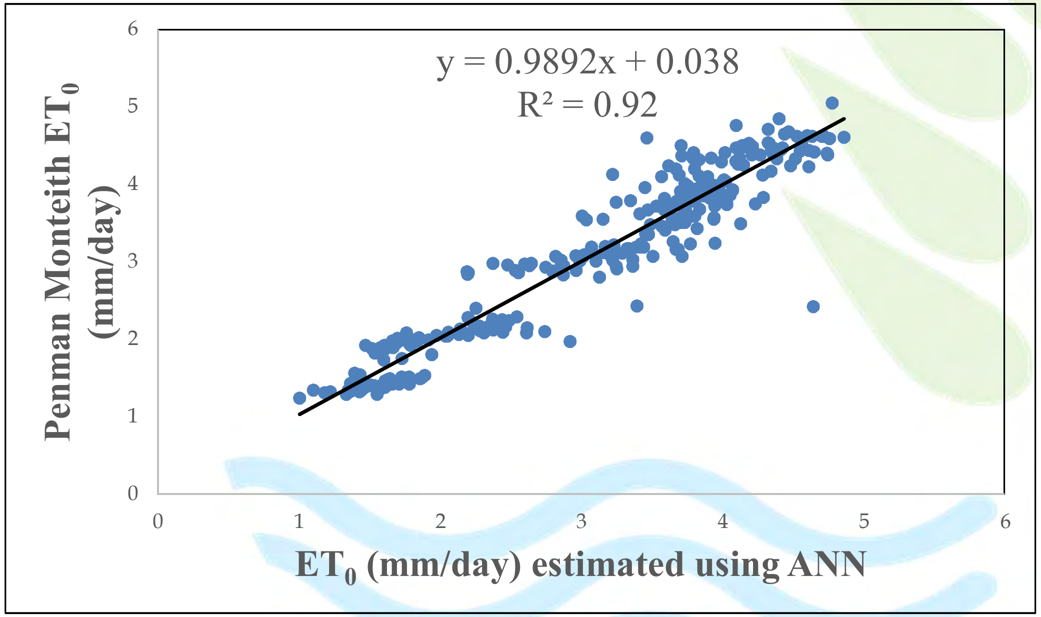


Fig 23. Performance of ANN in Training for Case 4

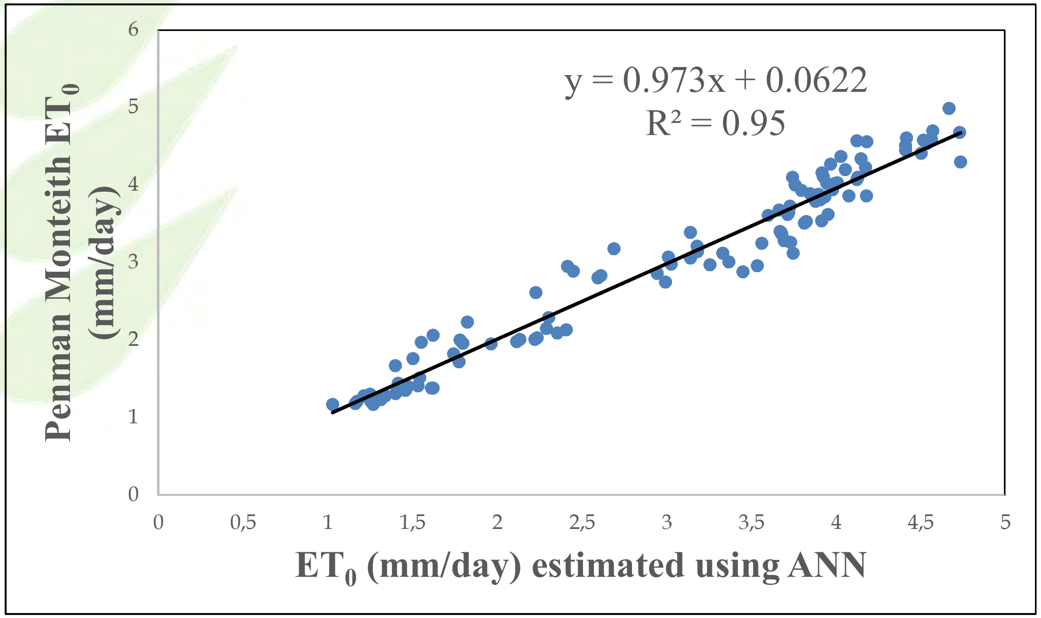


Fig 24. Performance of ANN in Training for Case 4

CONCLUSIONS

1. Estimated ET_0 using Modified Penman Method best correlates with the estimated ET_0 using Penman-Monteith Method with R^2 is equal to 0.87.
2. Estimated ET_0 using Pan Evaporation Method worst correlates with the estimated ET_0 using Penman-Monteith Method with R^2 equal to 0.62.
3. ANN is better than SVM and GPR for the estimation of ET_0 in all the cases considered for input data set as it shows better performance in testing with coefficient of determination (R^2) equals to 0.98 for Case 1, 0.96 for Case 2 and 0.95 for Case 3 and 4. For SVM, R^2 is 0.97, 0.92, 0.95 and 0.93 for Case 1, 2, 3 and 4, respectively. For GPR, R^2 is 0.97, 0.92, 0.94 and 0.94 for Case 1, 2, 3 and 4, respectively.

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4. Another purpose of this study was to determine the monthly difference between ET_0 and rainfall in the study area.
5. The result of the analysis shows that ET_0 surpasses the rainfall during the period from first week of October to the first week of June, which show that there is need for dependable options in the form of supplemental irrigation to meet the crop water requirements during drier months for getting the ultimate goal of sustainable agriculture.

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Thank You