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Evapotranspiration in Agri AI Tech: Analyzing Implementation of ANN Models

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1. Introduction

India is an agricultural country and most of the people depend on it for their livelihoods. Agriculture sector has a burden to fulfill the ever rising demand for food. There is a need to improve crop yield to meet rising food demands. There are several factors crop yield depends on like nutrient availability, water supply, ambient conditions, etc. Amount of water is the most important factor which is supplied to the crops. Hence, water management is very important, i.e., accurate estimation of needs for crop water.

A parameter is identified as potential or “reference evapotranspiration (ET_0)” by the “Food and Agriculture Organization of United Nations (FAO)” that can estimate crop’s water needs. It is calculated in mm/time as the loss of amount of water to evaporation from transpiration off the crop and soil. Radiation-based methods like Blaney-Criddle, Penman-Montieth (PM), and temperature-oriented approaches like Hargreaves are used to measure the same, where PM is the benchmark (Bogawski & Bednorz, 2014). It can calculate ET_0 when all the needed parameters are provided from weather stations and other temperature-oriented approaches can be helpful in non-availability. A lot of these techniques can be used to calculated approx. ET_0 value that could estimate final water needs. This is where Agri AI tech can be used to mimic the PM approach with least inputs (Nawandar et al., 2021). AI-based technologies can improve efficiency in the field of agriculture and overcome the issues like irrigation, crop yield, crop monitoring, soil sensing, weeding, etc. (Talaviya et al., 2020).

Evapotranspiration (ET) is among the major aspects of hydrologic cycle and it is very important to make accurate estimation for crop yield stimulation, hydrologic water balance, irrigation system management and design, and water resources management and planning. First of all, reference crop ET is estimated for calculating ET, i.e., alfalfa reference (ETr) or grass reference (ETo), from standard surface and "empirical crop coefficient" is applied. It accounts for difference among crop ET and standard surface.

It is possible to either estimate evapotranspiration with a water balance or lysimeter method or using climatological data. However, one cannot always measure evapotranspiration using lysimeter as it is time-consuming and needs well-planned and precise experiments. Hence ETo can be estimated with indirect approaches as per climatological data. These methods vary from empirical to complex relationships as per physical processes like combination method proposed by Penman (1948). Evaporation dynamics are linked with a flex of aerodynamic and net radiation features of natural surface in the combination approach.

As per the findings where latent heat transfer is affected in stems of the plant not just through such abiotic factors, a surface conductance term is introduced by Monteith (1965) which resulted in leaf stoma response to its hydrologic setting. This modified form is known significantly as "Penman-Monteith evapotranspiration model." ET is a non-linear and complex phenomenon which relies on various climatological aspects like wind speed, humidity, temperature, type, radiation, and crop growth, etc.

2. Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are effective for modeling of non-linear systems. ANN is a mathematical model with architecture similar to human brain. The "processing elements (PEs)" are highly interconnected and arranged in layers much like neurons are arranged in human brain. An ANN includes hidden, output, and input layers and each layer consists of a range of processing aspects. A neural network is connected well, which refers to the connection between each neuron in a layer with other neurons in succeeding layer.

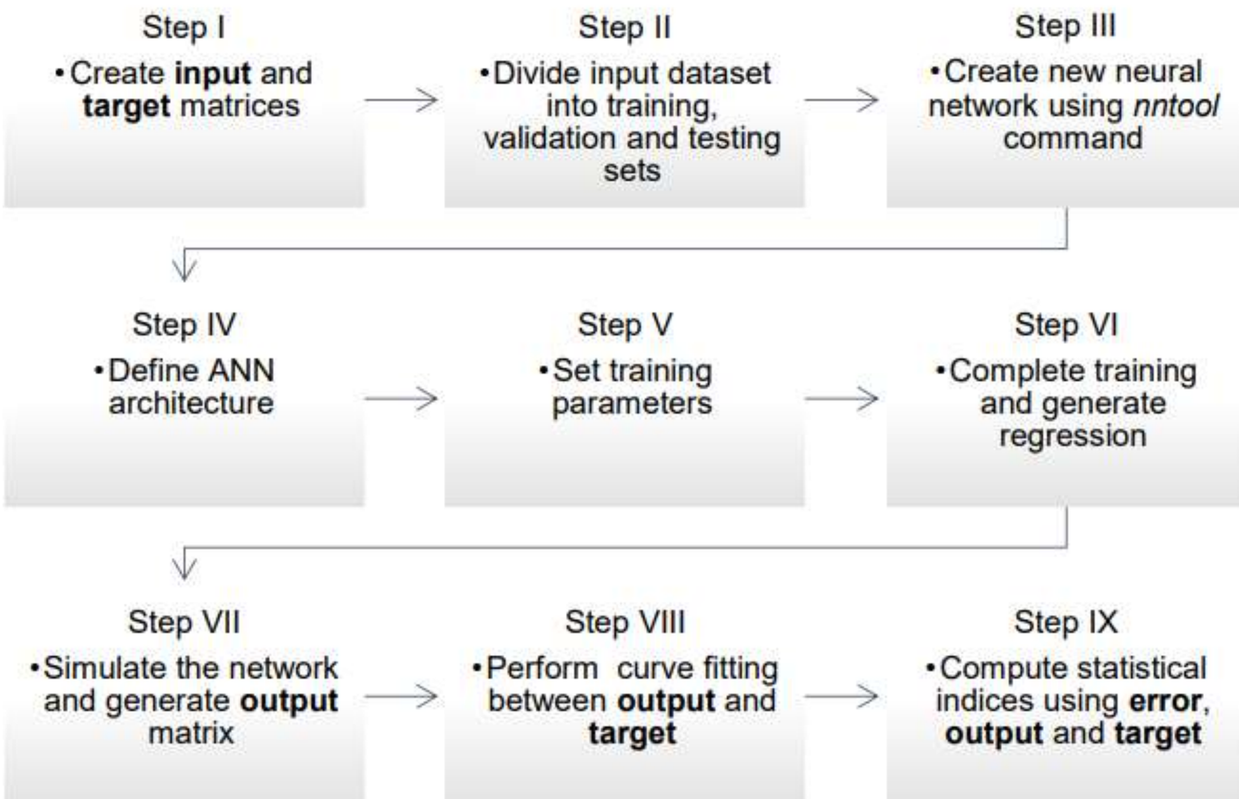
The components of PE are similar to the components of a neuron. The input layer consists of a range of input parameters and each variable of input looks like a neuron. A weight modifies each input whose functioning is similar to that of synaptic junction of a neuron. There are two parts of processing element. First one collects the subjective inputs and second one is a non-linear filter or activation function or transfer function. Activation function controls or squashes the output values of artificial neuron. Sigmoidal function is an activation function which is used most widely. It is a succeeding function varies eventually between 0 and 1 or 11 and 21 asymptotic values.

ANN learning is usually achieved with adaptive algorithm or procedure which adjusts weights of connections to improve the given performance. Along with data patterns, the neural network includes input and output (expected) values. The key here is to reduce the difference among expected and predicted output values with backpropagation model. There might be significant difference among the desired and predicted output values due to random assignment of weights to the connections. Hence, learning iteratively adjusts the connection weights to reduce such differences.

3. Implementing ANN Models for Evapotranspiration

Kumar et al. (2020) used two ANN models – A1 (5-5-1) and A2 (2-10-1). A1 was sufficient model with 5 input variables (relative humidity, minimum temperature, maximum temperature, solar radiation, and wind speed), 1 output node (ETo) and 5 hidden layer nodes. A2 was the limited model with only two inputs (maximum temperature and minimum temperature), 1 ETo output node, and 10 hidden layer nodes. A2 model was used to evaluate weather and ETo can be determined with temperature data only. They trained, generated, and tested all neural networks in MATLAB. They used log-sigmoidal function for activation transfer. The architecture relied on "trial and error" approach. After training and testing the network, researchers have generated a regression plot among target and output data for the given dataset. Later on, they validated the trained network for a new range of input variables to predict output from the deduced and hidden relationship. Figure 1 illustrates the process of ANN modeling.

Figure 1 – A Flowchart of step-by-step procedure of ETo Modelling



Source – Kumar et al (2020)

ANN Modelling Performance

Statistical indices are used to evaluate the efficiency of ANN modelling like "root mean square error (RMSE), coefficient of correlation (R), and mean absolute error (MAE). Here are the equations of these indices –

$$r = \frac{\sum_{i=1}^{n}(T_i - \bar{T})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{n}(T_i - \bar{T})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2}} \quad (1)$$

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

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$$MAE = \frac{1}{n}\sum_{i=1}^{n}|T_i - O_i| \quad (3)$$

Here,

Ti = Target ETo (mm day-1);

Oi = Output ETo (mm day-1);

$\bar{T}$ = Mean target ETo (mm day-1);

$\bar{O}$ = Mean target ET0 (mm day-1);

n = number of data points

4. Results

Once ANN models were trained, network training regressions were plotted. Output vector file was created at the phase of testing and both vectors were the part of performance evaluation and curve fitting indices. Apart from degree 1, researchers used polynomial-type fit for the best fit line. They performed the entire procedure for all sub-regions for both A1 and A2 models.

Model A1

With 5 parameters, Model A1 was used as input and came up with great results. ETo was estimated by the model and achieved significant agreement with Penman-Monteith FAO 56" estimates. Figures 2-4 illustrated the comparison between all three sub-regions and their ETo. A1 performed comparatively better in sub-regions SR-1 and SR-2 than in SR-3. Table 1 lists indices of statistical error to analyze the performance of both ANN models. Considering those statistical values, it is found that A1 achieved better performance in validation. In majority of incidences, R value was around 0.99. Hence, there is a significant correlation among ETo estimates of FAO-56 Penman-Monteith and ETo estimates predicted by A1.

Figure 2 – Association between ETo (PM) and ETo (ANN) during validation and calibration for A1 and SR-1

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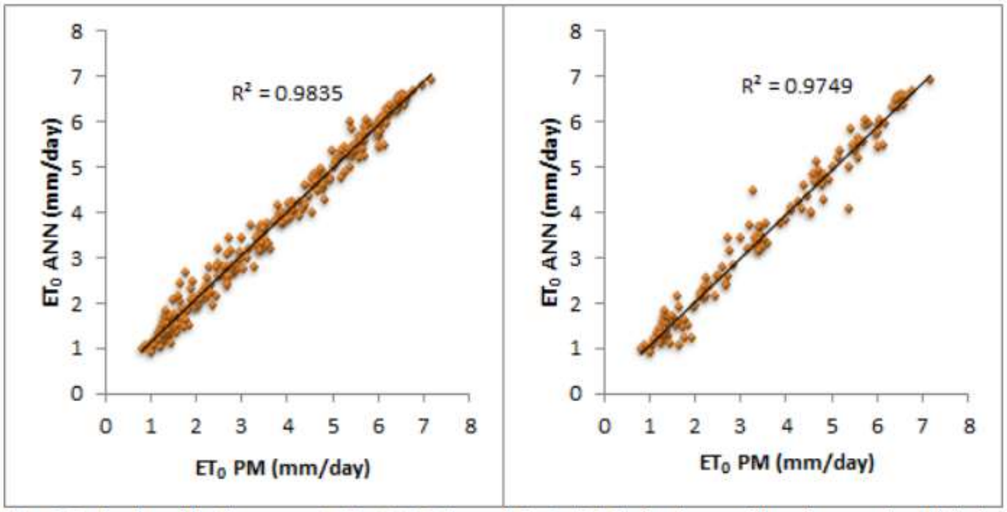
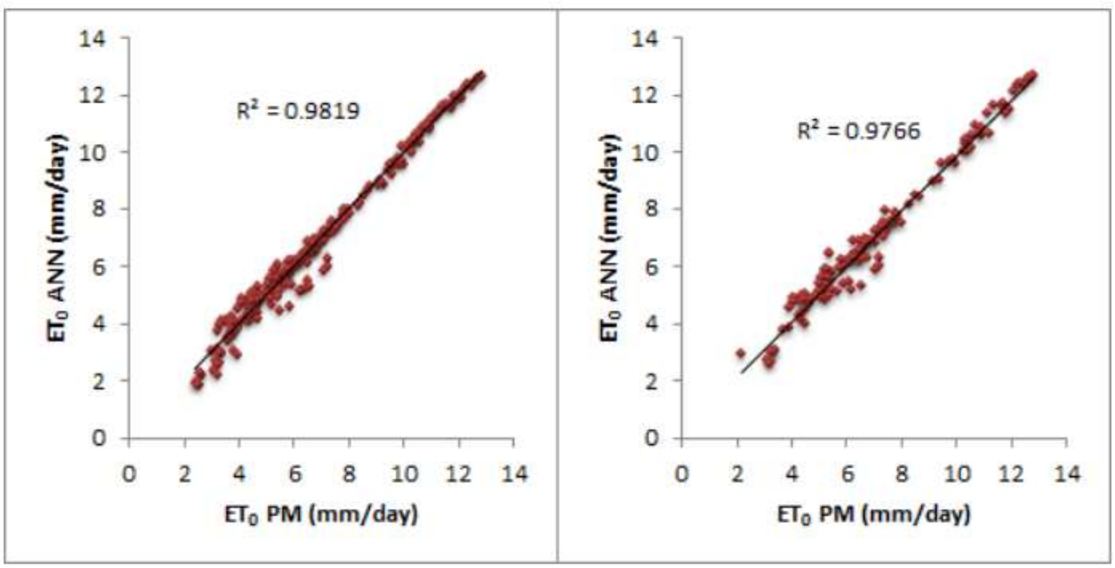


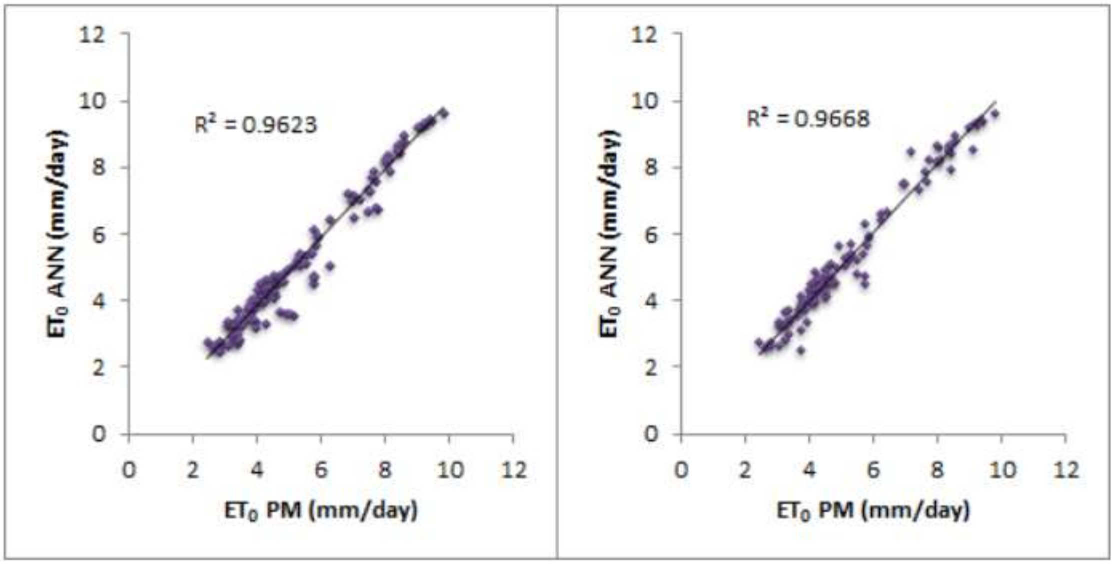
Source – Kumar et al. (2020)

Figure 3 – Association between ETo (PM) and ETo (ANN) during validation and calibration for A1 and SR-2



Source – Kumar et al. (2020)

Figure 4 – Association between ETo (PM) and ETo (ANN) during validation and calibration for A1 and SR-3

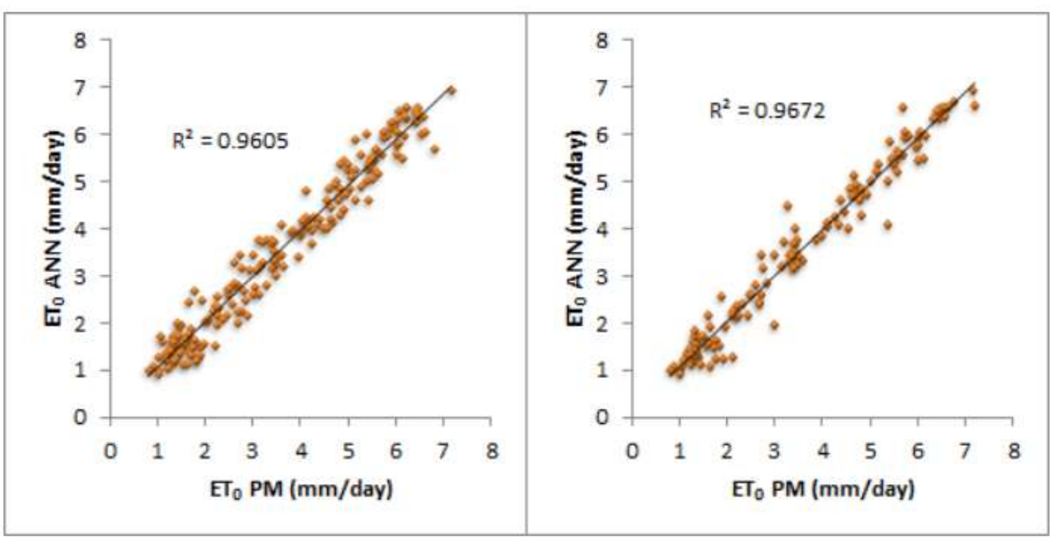


Source – Kumar et al. (2020)

Model A2

With just two input parameters, ANN model A2 showed commendable performance given its data requirement. However, the output was not that good but still reliable. For SR-1 and SR-2, the predictions were better than that of SR-3 (Figures 5-7). During calibration, model performance was better as given in “statistical error indices” (Table 1).

Figure 5 – Association between ETo (PM) and ETo (ANN) during validation and calibration for A2 for SR-1



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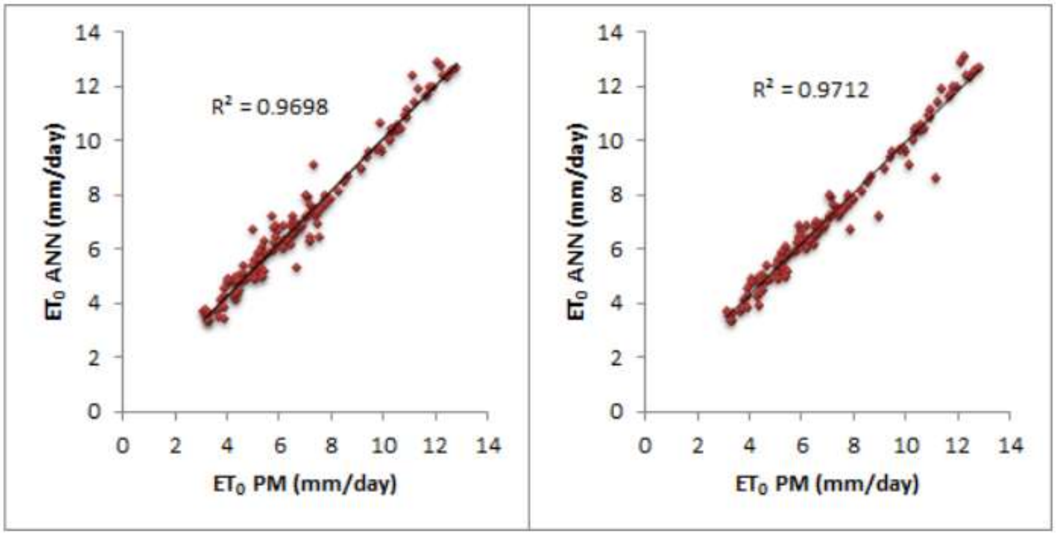
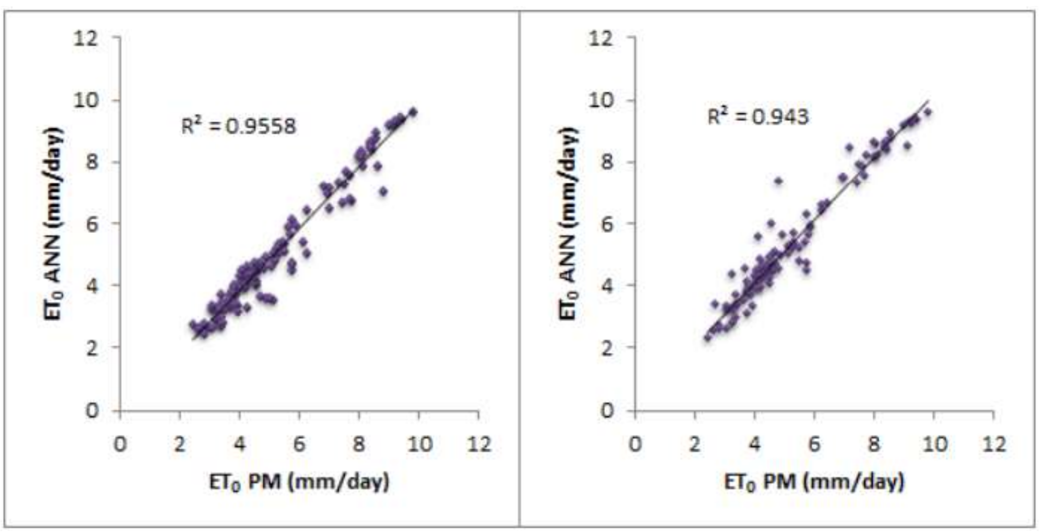
Source – Kumar et al. (2020)

Figure 6 – Association between ETo (PM) and ETo (ANN) during validation and calibration for A2 for SR-2



Source – Kumar et al. (2020)

Figure 7 – Association between ETo (PM) and ETo (ANN) during validation and calibration for A2 for SR-2



Source – Kumar et al. (2020)

Table 1 – Indices to evaluate performance of ANN modelling (Validation and Calibration) for each model and sub-region

Sub-region	ANN model	Statistical Index					
		Calibration			Validation		
		R (%)	*RMSE* (mm/day)	*MAE* (mm/day)	*R* (%)	*RMSE* (mm/day)	*MAE* (mm/day)
A1	M1	97.36	0.32	0.22	99.17	0.21	0.11
	M2	98.34	0.28	0.16	98.00	0.35	0.23
A2	M1	98.82	0.19	0.11	99.09	0.12	0.05
	M2	98.54	0.21	0.12	98.47	0.27	0.19
A3	M1	98.32	0.25	0.18	98.09	0.24	0.13
	M2	97.10	0.33	0.24	97.76	0.29	0.20

Source – Kumar et al. (2020)

5. Conclusion

Accurate estimation of crop water demands is very important to reduce loss of crops and avoid unwanted wastage of water supply. Potential estimation of evapotranspiration is the best way to estimate the water or irrigation demand. This study has proposed and discussed prediction of ETo with ANN models. This study presents the implementation of "Artificial Neural Network (ANN)" to compute the "reference evapotranspiration (ETo)" and uses "FAO-56 Penman-Monteith ETO" estimates to calculate its performance. Here, both ANN models showed better performance in validation instead of calibration stage. Though, A1 showed slightly better performance than A2, A2 was still reliable for estimation of ETo when there is lack of climatic data with reasonable accuracy level.

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