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Fanesh Kumar
Research Scholar, Department of Soil and Water Engineering, SVCAET&RS, IGKV, Raipur, Chhattisgarh, India

Jitendra Sinha
Professor, Department of Soil and Water Engineering, SVCAET&RS, IGKV, Raipur, Chhattisgarh, India

Vivek Kumar Tripathi
Director Research Services, IGKV, Raipur, Chhattisgarh, India

Nilima Jangre
SRF, National Hydrology Project (ISRO), ICAR- CIAE Bhopal, Madhya Pradesh, India

Corresponding Author:
Fanesh Kumar
Research Scholar, Department of Soil and Water Engineering, SVCAET&RS, IGKV, Raipur, Chhattisgarh, India

Assessment of rice water productivity for Pindrawan command area using ANN model and GIS

Fanesh Kumar, Jitendra Sinha, Vivek Kumar Tripathi and Nilima Jangre

Abstract

Agriculture is the largest consumer of water through evapotranspiration and percolation. Irrigated agriculture remains the largest user of water globally, which may increase the risk of water scarcity for agricultural sector in the future. So, there is an immense need for enhancing per drop more crop. The present study focuses on assessment of rice water productivity for Pindrawan command area using ANN model and GIS. 20 years meteorological data and crop coefficient (K_c) of rice at different crop growth stages were analyzed to estimate crop evapotranspiration (ET_C). Production and productivity data of the study area were obtained from the Agriculture Department Government of Chhattisgarh. The values of Crop Water Productivity (CWP) using ANN models (A1, A2 and A3) ranged A1(0.583- 0.615), A2 (0.582-0.614) and A3 (0.573-0.604) kg-m^{-3}, while Field Water Productivity (FWP) ranged A1(0.329-0.347), A2(0.329-0.347), A3(0.326-0.344) kg-m^{-3} in study area. The values of CWP as estimated by CROPWAT and ANN models were found to be quite close. However, the ANN models estimated CWP little higher side (3.21%). Three different ANN models have been integrated in this study, depending on the combination of inputs to be given to the network. The first model (A1PC) has six inputs, the second model (A2PC) only has 4 inputs and third model (A3PC) only has 2 inputs. Performance evaluation of the models has been carried out by calculating the mean absolute deviation (MAD), root mean square error (RMSE), Absolute Prediction Error (APE), coefficient of correlation (CC), Nash-Sutcliffe coefficient efficiency (CE), and Index of Agreement (IOA).

Keywords: Artificial neural network, water productivity, consumptive water use, reference evapotranspiration

Introduction

Water, is our most important natural resources, which is scarce at certain times and at certain places. The scarcity of water, regarded as the most important factor in crop production, is usually a limiting factor in the development of irrigation scheme particularly in semiarid regions. Irrigation scheduling is the process of supplying the needed amount of water for crops at the most appropriate time so that soil water content never falls below the allowable depletion level to avoid the crop stress, thus maximizing the yield. Another important objective of maximize irrigation efficiency by minimizing runoff and percolation, losses and in turn, saving water and energy. There is an urgent need to enhance more crop per drop as envisioned in the *Pradhan Mantri Krishi Sinchai Yojana* (PMKSY).

Water productivity in agriculture tries to enhance food production while using the same quantity of water or producing the same amount with less water. It considers the advantages and costs of water use in terrestrial and aquatic ecosystems, with the goal of producing more food, earning more money, improving livelihoods, and providing ecological benefits at a lower social and environmental cost per unit of water consumed. Water productivity is the quantity of crop yield per unit of total water used in the agricultural production process, taking into account all types of water losses. Definition of water productivity also changes with the background of the researcher or stakeholder involved (Kar *et al.*, 2016) [6].

Artificial Neural Networks (ANN) are high-performance computing systems that biological neural networks. They consist of interconnected neurons working in parallel, each with an activation signal. ANNs are powerful tools for modeling nonlinear systems, making them easier to use than climatological models. MATLAB is a highly efficient numerical computation and visualization software with hundreds of built-in functions for technical computation, graphics, animation, and interactive environments.

Artificial Neural Network for daily reference crop estimation ET_o was calculated using evapo-transpiration (ET_o), and the effectiveness of ANNs was compared to that of the traditional approach (Penman Monteith). The number of processing components in the hidden layer(s), the number of hidden layers, and various learning techniques were some of the concerns related to the usage of ANNs that were investigated. Three learning strategies were taken into consideration, back propagation with momentum and normal back propagation (Kumar *et al.* 2002) [7]. Evaporation is a complex and non-linear phenomenon due to its dependence on various climatological factors. (Bai *et al.* 2017) [1] studied the evapotranspiration rate from a reference surface, commonly known as ET_0, is the evapotranspiration rate from a hypothetical grass reference crop with an assumed crop height of 0.12 m, fixed surface resistance of 70 sec/m, and albedo of 0.23.

ANNs are powerful tools for modeling nonlinear systems and can simulate human cognitive responses. A neural network is a network of neurons that can determine the input-output relationships of a complex process. 20-years climatic data were analyzed with the CROPWAT model, which is based on the United Nations Food and Agriculture Organization (FAO) paper number 56 (FAO 56). (Jangre *et al.* 2022) [5] applied the Penman-Monteith method was used to estimate reference evapotranspiration (ET_0). Crop coefficient (K_c) from the phenomenological stage (initial, development, mid-season, and late-season) of rice were applied to adjust and estimate the actual evapotranspiration ET_c through a water balance of the irrigation water requirements (IR).

Rice, a rainy, humid plant, is a significant global crop, accounting for 40% of global irrigation and 17% of groundwater depletion. It requires an average of 2,500 liters of water per kilogram. Drip irrigation has been found to be more water-efficient than conventional methods, reducing water use, growth, and yield. Sonit *et al.*, (2017) [4] applied drip irrigation with IW: CPE - 1.2 to 1.4 in summer paddy and concluded that it is superior than flooding in relation to water use efficiency. Though rice is a water guzzling crop but it is not and aquatic plant and drainage is also required if there is an excess of water in the field. Sinha *et al.*, (2013) [8] studied the provision of drainage in rice field along with the conjunctive use of surface and groundwater and found the yield of rice to be increased from 4.9 to 5.7 q ha^{-1}.

Water productivity is influenced by crop evapotranspiration and yield, and the Geographic Information System (GIS) provides a platform for mapping water productivity in a command area. GIS mapping involves displaying multiple layers of information on a single map, including aerial views, areas of interest, and statistical data about neighborhoods like production, fertility, and stream density.

Materials and Methods

Description of study area

The research was carried out at the Pindrawan Command Area (PCA) in the upper Mahanadi River valley, in the southeastern part of Raipur district, Chhattisgarh, India. The study area is on Toposheet No. 64 G/15, with latitude ranging from 21°24'14" N to 21°29'27" N and longitude ranging from 81°44'12" E to 81°53'48" E. The Pindrawan Tank Scheme is a Medium Irrigation Project of the Government of Chhattisgarh. The irrigation scheme includes 2419 ha of *Kharif* land in *Tilda* and *Dharsiwa* blocks, with two distributaries (*Saragaon* and *Siliyari*) and 12 minors as shown in Fig. 1.

Data Organization

The climate data on maximum temperature (T_{max}), minimum temperature (T_{min}), relative humidity (RH), wind speed (WS), sunshine hour (SS), and rainfall (RF) were collected from Collection of Department of agrometeology, IGKV, Raipur (C.G.). Crop data collected through the field survey was carried out for the collection of data on major crop varieties grown by the local farmers. The data has been collected via oral questionaries and includes information on the package of practices for crop cultivation, irrigation requirements. Collection of soil dataWhile sampling the soil of the command area, colour, texture and cropping pattern of the area were all considered.

Water Productivity (WP)

Water Productivity (WP) have been attempted to understand the quantity of output generate (Yield) in relation to the consumptive water use (CWU). The WP was estimated by using following equation. Crop water productivity (CWP) It is one kilogram of produce per cubic meter of water consumed through evapotranspiration during crop growth, kg/m^3. Field water productivity (FWP) is a ratio between marketable crop yield and field water supply which includes water used by the plant in metabolic activities, evapotranspiration and percolation.

$$\text{WP} = \frac{\sum_{\text{crop}} \text{Average Yield X } (\text{Area}^{\text{IR}} + \text{Area}^{\text{RF}})}{\text{CWU}} \qquad (1)$$

Where, WP is the water productivity (kg m^{-3}), $Area^{IR}$ is the irrigated area, $Area^{RF}$ is the rainfed area, CWU is the consumptive water use (m^3).

Estimation of ET_0 using FAO penman monteith method

The evapotranspiration rate from a reference surface, not short of water, is called reference evapotranspiration (ET_0). Cropwat 8.0 uses the Penman (1948) [9] and Monteith (1965) [10] method to calculate reference evapotranspiration (ET_0) using temperature humidity, wind speed and sunshine hours. The mathematical expression of the reference evapotranspiration is as follows:

$$ET_0 = \frac{0.408\,\Delta\,(R_n - G) + 900\,\gamma u_2 \frac{(e_s - e_a)}{(T+273)}}{\Delta + \gamma\,(1 + 0.34\,u_2)} \qquad (2)$$

Where;
ET_0 = Reference evapotranspiration [mm day^{-1}]
R_n = Net radiation [MJ m^{-2} day^{-1}]
G = Soil heat flux density [MJ m^{-2} day^{-1}]
T = Mean daily air temperature at 2 m height [°C]
u_2 = Wind speed at 2 m height [m s^{-1}]
e_s = Saturation vapour pressure [kPa]
e_a = Actual vapour pressure [kPa]
e_s - e_a = Saturation vapour pressure deficit [kPa]
Δ = Slope of the vapour pressure curve [kPa $°C^{-1}$]
γ = Psychrometric constant [kPa $°C^{-1}$]

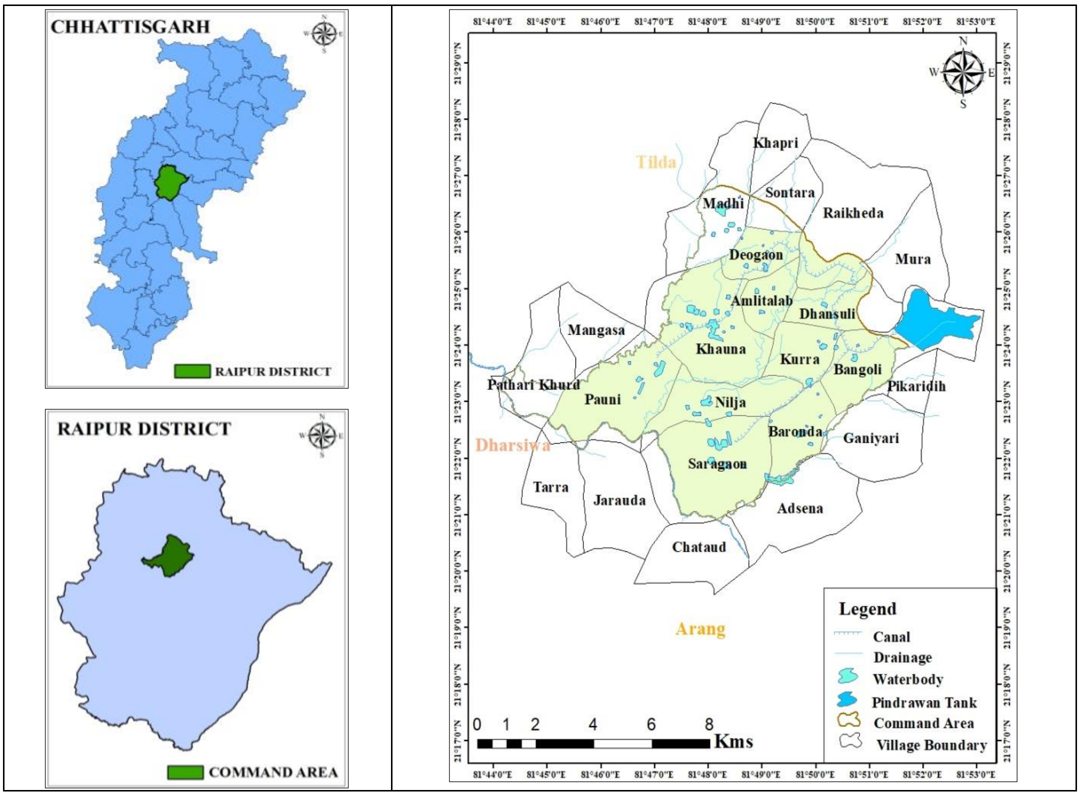

Fig 1: Location map of the study area

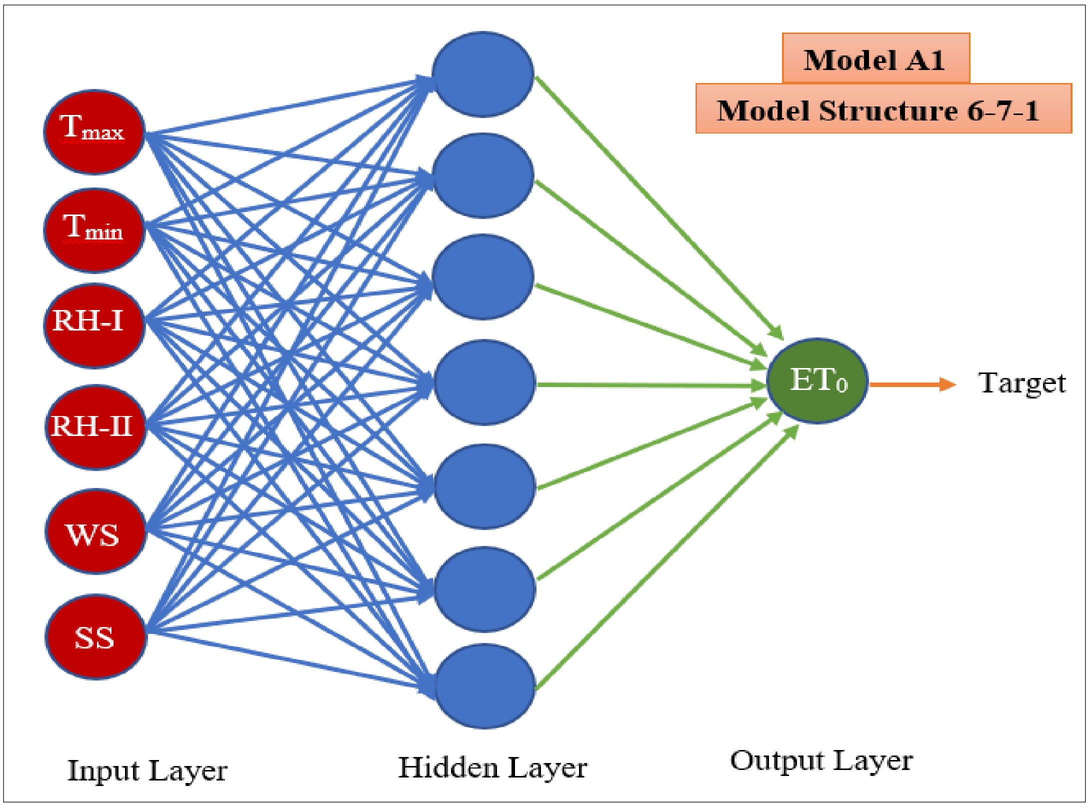

Fig 2: Network architecture of ANN model A1PC

Crop Production

Data on crop production was collected from the network of Rural Agricultural Extension Officers. The field officers, or RAEOs, are in the role of collecting primary data on agricultural production. The process involves for choosing one-fourth of the farmers in a particular area, then choosing five square meters of each farmer's fields. The primary data used to calculate the productivity per hectare is the production from each of these fields. This formula is also used to determine the village's average production of crops.

Consumptive Water Use (CWU)

Consumptive Water Use (CWU) for a crop is the sum of the amount of water that a crop transpires during the course of its growth and amount of water that evaporates from the surface on which the crop is cultivated. EI-Marsafawy *et al.*, (1998) [2] found that the ratio between the water consumption and crop evapotranspiration ET_c estimated by the three formulas namely Modified Penman, Penman-Monteith, and Doorenbos-Pruitt were 1.05, 1.02, and 0.95 respectively. Therefore, the calculated value of ET_c is used in this research to determine crop CWU.

Development of Artificial Neural Network model

Daily meteorological data such as maximum temperature (T_{max}), minimum temperature (T_{min}), relative humidity (RH), wind speed (WS), and sunlight hour (SS) were used as inputs for ANN modelling. Three different ANN models have been integrated in this study, depending on the combination of inputs to be given to the network. The first model (A1) has six inputs: maximum temperature, minimum temperature, relative humidity (I and II), wind speed, and sunshine hour. The second model (A2) only has 4 inputs: maximum temperature, minimum temperature, wind speed, and sunshine hour, whereas the third model only has 2 inputs: maximum temperature and minimum temperature as shown in Fig.2.

Performance evaluation of Artificial Neural Network model

Performance evaluation of the models has been carried out by calculating the mean absolute deviation (MAD), root mean square error (RMSE), Absolute Prediction Error (APE), coefficient of correlation (CC), Nash-Sutcliffe coefficient efficiency (CE), and Index of Agreement (IOA). The network is selected based on maximized CC, CE, and IOA values and minimized MAD, RMSE, and APE values, both in training and testing. The network parameters (weights and biases) were estimated using a standard back propagation approach. Because the activation function employed in the hidden and output nodes is a sigmoid function, the values were scaled to lie between 0 and 1.

Results and Discussion

To estimate crop water productivity, long term (20 years) of climatological data from the study area were analyzed in ANN. The crop considered in this study is rice (variety: *Swarna- Sub1*), which is predominantly grown in the command area during the *Kharif* season and has an average sowing date of 23rd June and an average harvesting date of 14th November. There are four different stages of rice growth in the command area: the initial stage (25 days duration), the development stage (40 days duration), the mid-season stage (60 days duration), and the late season stage (20 days duration). The crop coefficient values (K_c dry and K_c wet) differs in various stages. In this study, the average value of K_c dry for land preparation has been adopted by software as 0.5, while the K_c value suggested by CROPWAT (FAO-56) at different stages, *viz.* the initial stage, development stage, mid-season stage, and late-season stage the K_c value is taken as 0.5, 1.05, 1.05, and 0.7 respectively. Similar to this, software suggests K_c wet values of 1.05 for land preparation and 1.1, 1.3, 1.3, and 0.6 for different stages.

Architectures for Artificial Neural Network model

This study incorporates three different ANN models (A1, A2, and A3), depending on the combination of inputs to the network. For the Pindrawan command area, the A1PC (A1 Model of Pindrawan Command) model has been created. The final model structure (A1PC) in terms of number of layers, number of input neurons, number of hidden neurons, number of output nodes, and number of iterations was “3-6-7-1-500” with normalized sum squared error ‘sse’ performance of 0.41. At this stage, the model was considered generalized. It was shown that a greater number of iterations was causing overlearning by the network. Similarly, the final model structures A2PC (the A2 model of Pindrawan command) and A3PC (the A3 model of Pindrawan command) were found to be “3-4-7-1-500” and “3-2-7-1-500” with normalized ‘sse’ performance of 1.53 and 7.41, respectively as depicted in Table 1.

Table 1: Performance of best ANN models

Parameters	A1PC Model		A2PC Model		A3PC Model	
	Training	Testing	Training	Testing	Training	Testing
MAD	0.09	0.13	0.18	0.19	0.42	0.51
RMSE	0.13	0.19	0.25	0.27	0.55	0.66
CC	0.99	0.98	0.97	0.96	0.83	0.79
CE	0.98	0.96	0.94	0.92	0.69	0.49
IOA	1.00	0.99	0.98	0.98	0.90	0.85
APE	0.03	0.04	0.05	0.06	0.12	0.15

BPANN was created using MATLAB programs. In MATLAB, a program was written, edited, debugged, and run. The program was appropriately updated to support various input patterns and models. The program is adaptable to alternative activation functions (tansig, logsig, and purelin), performance functions (mse, sse, and msereg), training algorithms (trainbr, trainlm, etc.), and iterations. The application accepts input data files in the 'delimited text files without header' format with the standard extension 'txt' and outputs data in the same manner. The output file was then converted to a fixed-width MS Excel' file. The 'logsig' activation function was used in this investigation. The Levenberg-Marquardt (trainlm) training algorithm was used, and the performance function was ‘sse’.

Crop water productivity using Artificial neural network

The crop water productivity as worked out from different ANN model in the average of 20 years and 11 different villages in the PCA. The crop evapotranspiration (ET_c) for *Kharif* rice was found at 572.4 mm, 573.2 mm and 583.5 mm for model A1PC, A2PC and A3PC respectively. The maximum consumptive water uses (in *Khauna* village) from 4275804 m^3, 4281218 m^3 and 4350749 m^3 and minimum consumptive water uses (in *Pouni* village) from 286457 m^3, 286820 m^3 and 291478 m^3 for model A1PC, A2PC and A3PC respectively. The maximum CWP was found at 0.615, 0.614 and 0.604 kg m^{-3} in the village of *Raikheda*, while the minimum was found at 0.583, 0.582 and 0.573 kg m^{-3} in the village of *Dhansuli* for model A1PC, A2PC and A3PC respectively as depicted in Table 2.

Field water productivity using Artificial Neural Network

The Pindrawan command area of field water productivity was calculated using various ANN models. For models A1PC, A2PC, and A3PC, the crop evapotranspiration (ETc) for *Kharif* rice was found to be 572.4 mm, 573.2 mm, and 583.5 mm, respectively. The highest consumptive water uses (in *Khauna* village) range from 7574445 m^3, 7579859 m^3, and 7649390 m^3, while the lowest consumptive water uses (in *Pouni* village) range from 507450 m^3, 507812 m^3, and 512471 m^3. In the villages of *Raikheda* and *Dhansuli*, the maximum and minimum FWP values for the models A1PC, A2PC and A2PC were found to be 0.347, 0.347 and 0.344 kg m^{-3} and 0.329, 0.329 and 0.326 kg m^{-3}, respectively as shown in Table 2. CWP and FWP maps display spatial variation in water productivity in a command area. Areas with higher WP is depicted in 'dark colors' and underperforming areas in 'light colors'. The respective areas are also linked to canal lines, tanks (reservoirs), villages, command area boundaries, and other spatial information are shown in Fig. 3 and Fig 4.

Table 2: Estimation of long time CWP and FWP of different ANN models

Villages	Area (ha)	Yield (kg/ha)	CWU (m^3)			CWP (kg/m^3)			TCWU (m^3)			FWP (kg/m^3)		
			A1PC	A2PC	A3PC	A1PC	A2PC	A3PC	A1PC	A2PC	A3PC	A1PC	A2PC	A3PC
Bangoli	221.2	3803	1396897	1398666	1421382	0.602	0.602	0.592	2474557	2476326	2499042	0.340	0.340	0.337
Dhansuli	166.9	3682	1053753	1055088	1072223	0.583	0.582	0.573	1866689	1868023	1885159	0.329	0.329	0.326
Kurra	306.6	3783	1935717	1938168	1969646	0.599	0.598	0.589	3429058	3431509	3462987	0.338	0.338	0.335
Baronda	228.7	3819	1444176	1446005	1469489	0.605	0.604	0.595	2558310	2560139	2583623	0.341	0.341	0.338
Nilja	257.1	3745	1623277	1625333	1651730	0.593	0.592	0.583	2875582	2877638	2904035	0.335	0.335	0.332
Saragaon	165.6	3839	1045514	1046837	1063839	0.608	0.607	0.598	1852093	1853417	1870418	0.343	0.343	0.340
Raikheda	136.9	3881	864543	865638	879697	0.615	0.614	0.604	1531510	1532605	1546663	0.347	0.347	0.344
Deogaon	89.4	3837	564593	565308	574489	0.608	0.607	0.597	1000158	1000873	1010054	0.343	0.343	0.340
Amlitalab	123.6	3854	780593	781581	794275	0.610	0.610	0.600	1382795	1383783	1396477	0.345	0.344	0.341
Khauna	677.2	3861	4275804	4281218	4350749	0.611	0.611	0.601	7574445	7579859	7649390	0.345	0.345	0.342
Pouni	45.8	3868	286457	286820	291478	0.613	0.612	0.602	507450	507812	512471	0.346	0.346	0.342
Average	219.9	3815.6	1388302.2	1390060.2	1412636.1	0.604	0.604	0.594	2459331.5	2461089.5	2483665.4	0.341	0.341	0.338
S.D.	169.5	59.7	1070577.4	1071932.9	1089342.1	0.010	0.010	0.009	1896492.1	1897847.8	1915257.0	0.005	0.005	0.005
C.V.	77.09	1.56	77.11	77.11	77.11	1.58	1.60	1.57	77.11	77.11	77.11	1.58	1.56	1.55

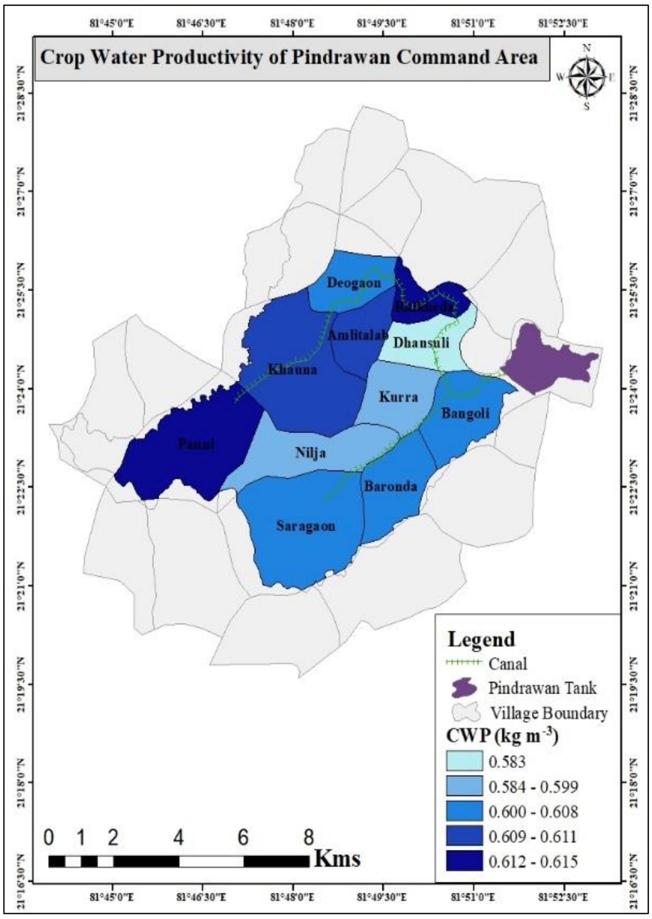

Fig 3: CWP A1PC Model

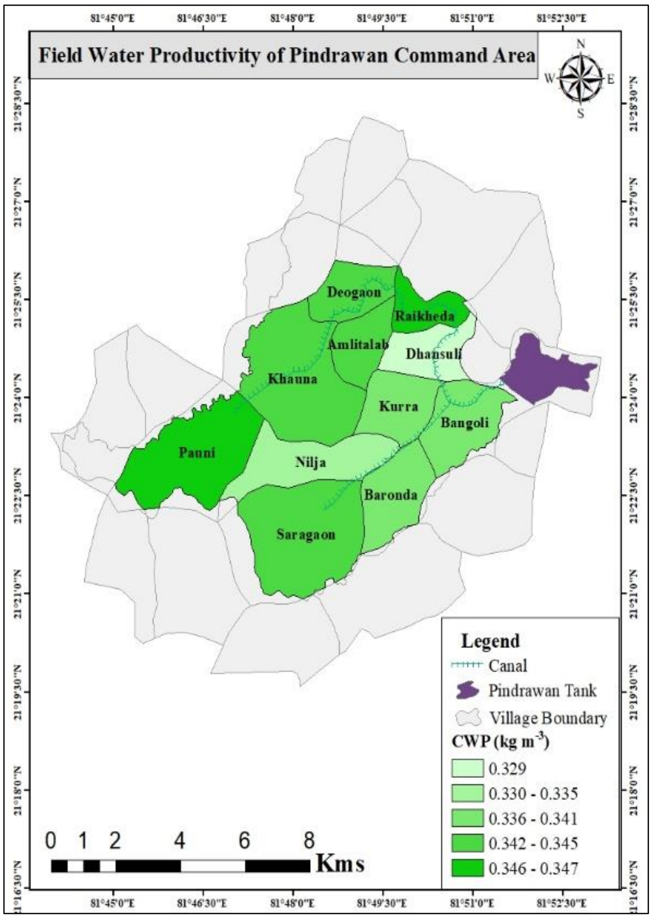

Fig 4: FWP A1PC Model

Statistical Parameters

Artificial neural network technique instead of a multi-linear regression approach has several advantages, including increased model flexibility and the ability to set relative weights to each connection of the input variables. The regression line for the A1PC model with the temperature as input is plotted for the training 6 -input stages of ANN. In this phase of ANN, the training phase of Neural Network which gave R^2 value of 0.9826 and in the testing phase which gave R^2 value of 0.9596. A regression line for the A2PC model, the 4-input of ANN, the training phase of Neural Network which gave R^2 value of 0.9371 and in the testing phase which gave R^2 value of 0. 6188. Similarly, for A3PC model, the training phase of Neural Network which gave R^2 value of 0.6939. and in the testing phase which gave R^2 value of 0.9215. The relationship (Scatter plot) of the A1PC, A2PC, and A3PC ANN models with the CROPWAT model for Rice of the Pindrawan command area during the training and testing periods is shown in Fig 5 and Fig. 6.

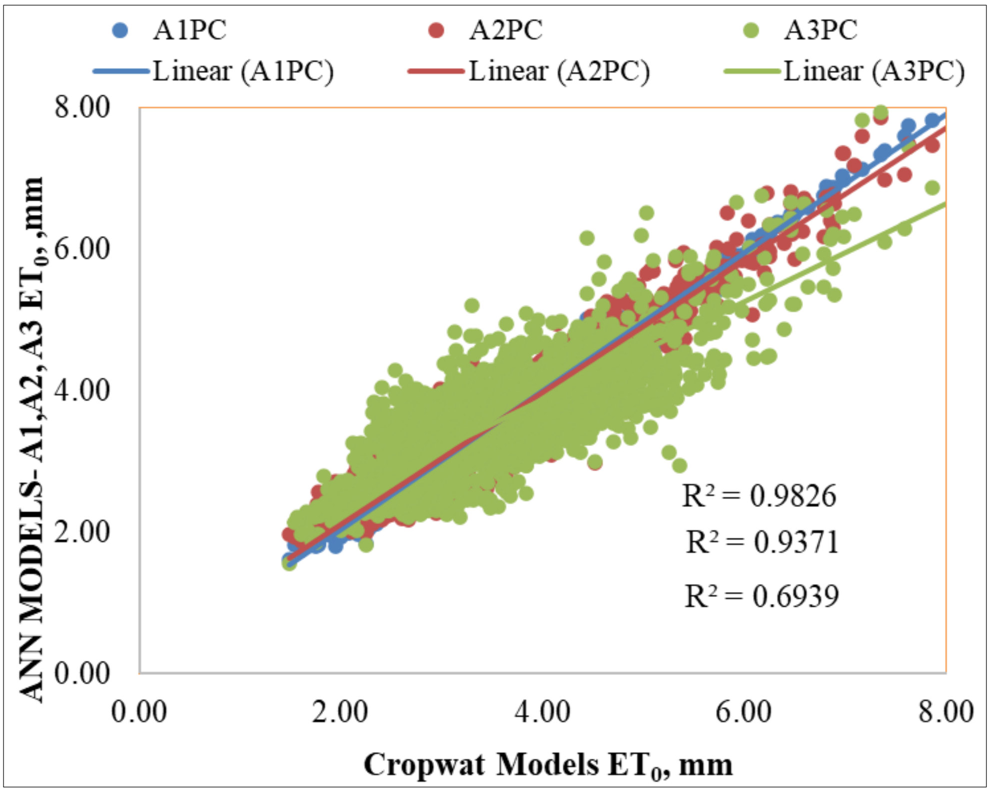

Fig 5: Relationship between A1PC, A2PC, A3PC models for PCA in Compirition with Cropwat Model for training period

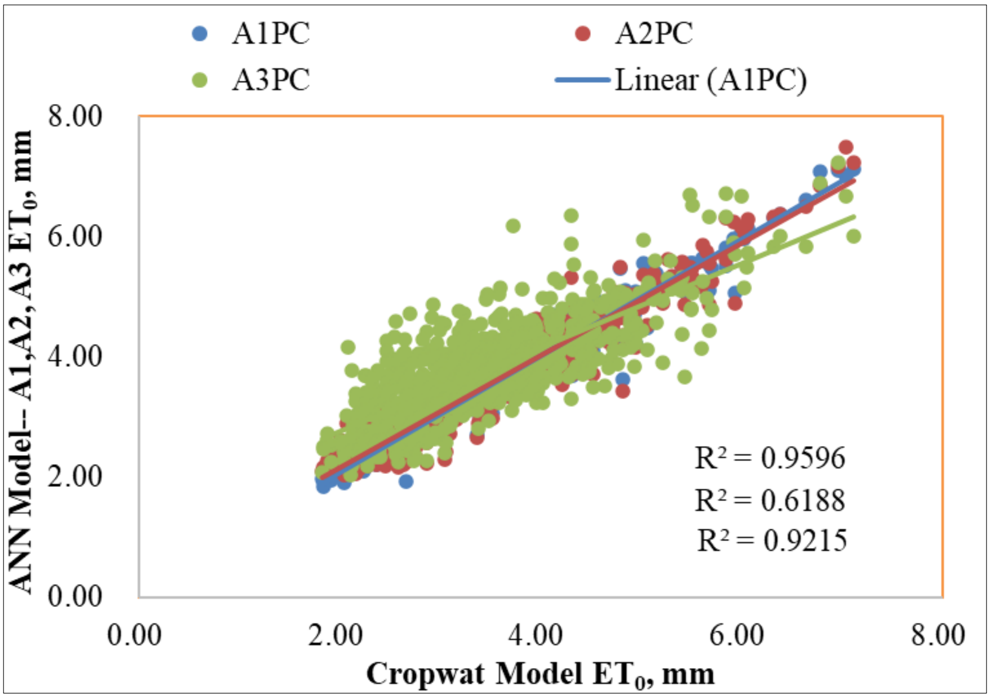

Fig 6: Relationship between A1PC, A2PC, A3PC models for PCA in Compirition with Cropwat Model for testing period

Comparison of Artificial Neural Network and CROPWAT model

The output is in conformity with the compression of ANN *viz*, A1PC, A2PC, A3PC models and Cropwat model for estimation of average crop evapotranspiration of *Kharif* rice for Pindrawan tank command area (PCA) is presented in Table 3. The compression is made the basis of percentage variation with respect to value computed by Cropwat model. It is clear from the table that the variations of percentages for evapotranspiration as 3.66%, 3.51% and 1.69% for models A1PC, A2PC and A3PC, respectively. The variation for A3PC model is low as compare to A1PC and A2PC model. The estimated value of rice water productivity by different model of ANN (A1PC, A2PC and A3PC) are very well associated with the value of computed from Cropwat Model.

Table 3: Performance evaluation of ANN and CROPWAT model

Year	Cropwat Model, ET_c	ANN Model, ET_c			Percentage of Variation, %		
		A1PC	A2PC	A3PC	A1PC	A1PC	A1PC
2001	578.3	570.5	572.1	572.9	1.37	1.09	0.94
2002	637.2	633.5	627.8	601.8	0.58	1.49	5.88
2003	545.3	532.5	539.2	536.7	2.41	1.12	1.61
2004	605.8	594.5	593.8	577.5	1.90	2.02	4.89
2005	554.2	542.2	541.4	535.6	2.21	2.36	3.47
2006	597.9	596.4	592.7	560.5	0.26	0.88	6.67
2007	556.5	554.1	556.6	552.9	0.43	-0.01	0.65
2008	595.2	584.4	576.8	574.3	1.85	3.19	3.64
2009	635.9	629.1	631.3	626.4	1.09	0.74	1.52
2010	575.4	587.7	590.0	598.0	-2.09	-2.48	-3.78
2011	557.7	552.4	554.1	569.0	0.97	0.66	-1.98
2012	532.3	535.5	538.2	550.0	-0.59	-1.09	-3.21
2013	685.9	513.9	514.6	530.9	33.46	33.28	29.19
2014	739.2	591.7	592.7	611.0	24.93	24.73	20.98
2015	620.7	625.9	627.6	634.3	-0.83	-1.10	-2.14
2016	620.7	551.2	552.2	576.7	12.60	12.40	7.63
2017	562.8	563.6	559.5	626.7	-0.14	0.59	-10.19
2018	547.4	538.6	543.5	587.0	1.64	0.72	-6.74
2019	554.8	564.6	569.6	605.6	-1.74	-2.59	-8.39
2020	564.1	586.6	591.3	642.3	-3.83	-4.59	-12.17
Average	593.4	572.4	573.2	583.5	3.66	3.51	1.69

Conclusions

The long term (20 years) rice water productivity (CWP) and field water productivity (FWP) of the command areas was assessed using scientific tools Artificial Neural Network. The study will be helpful to increase the yield per unit area by reducing unproductive water outflows and depletion from seepage and percolation losses and thus making effective use of rainfall. The results of this study can be used by agriculturists and water resource planners, helping to conserve water and guiding farmers on how much water is required in the field for crop production.

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