Journal of Agrometeorology
ISSN : 0972-1665 (print), 2583-2980 (online)
Vol. No. 26 (1) : 56 - 62 (March - 2024)
https://doi.org/10.54386/jam.v26i1.2247
https://journal.agrimetassociation.org/index.php/jam

Research Paper

Evaluation of soft-computing techniques for pan evaporation estimation

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ABSTRACT

Estimation of pan evaporation (E_{pan}) can be useful in judicious irrigation scheduling for enhancing agricultural water productivity. The aim of present study was to assess the efficacy of state-of-the-art LSTM and ANN for daily (E_{pan}) estimation using meteorological data. Besides this, the effect of static time-series (Julian date) as additional input variable was investigated on performance of soft-computing techniques. For this purpose,the models were trained, tested and validated with eight meteorological variables of 37 years by using preceding 1-, 3- and 5- days' information. Data were partitioned into three groups as training (60%), testing (20%), and validation (20%) components. It was observed that the models performed well (best) with preceding 5-days meteorological information followed by 3-days and 1-day. However, all LSTMs simulated peak value of (E_{pan}) was more accurate as compared to lower values. Meteorological data with julian date improved the performance of LSTMs (0.75<NSE1; PBias<10; KGE 0.75). The ANN trained using only meteorological data (preceding 5-days information) had better performance error statistics among all other ANNs and LSTMs with minimum MAE (0.68 to 0.86), RMSE (0.93 to 1.22), PBias (-0.73 to 2.44) and maximum NSE (0.83 to 0.84) and KGE (0.89 to 0.92). Overall, it was inferred that the forecasting of meteorological parameters using a few days preceding information along with Julian date as the time series variables resulted in better estimation of (E_{pan}) for the study region.

Keywords: Evaporation, Irrigation, Neural network, Irrigation scheduling, LSTM network

Agricultural production is primarily dependent on the effective utilization of the available water resources, especially under drought-prone, dry, sub-humid and semi-arid climatic regions (Sharma *et al.,* 2021). Measurement or accurate estimation of evaporation losses plays a significant role in reservoir management, development of irrigation and drinking water supply systems particularly in drought-prone areas towards improving agricultural productivity and efficient water resource management, (Kim *et at.,* 2015). Generally, there are two main approaches *viz.* direct methods and indirect methods. Direct methods include the class A pan, class U pan, and lysimeter. However, the class A pan evaporation is widely used as compare to other methods (Bicalho *et al.,* 2016: Kingra *et al.,* 2002). Indirect techniques comprise evaporation determination using meteorological information and physical conceptslike volume and energy conservation that require precise adjustment based on climate. (Abed *et al.,* 2022, Chowdhury *et al.,* 2010).

Considering the limitations associated with both measurement and empirical approaches for evaporation estimation, use of soft computing techniques is being applied during last decades for estimating stochastic different hydrological and climatological parameters (Terzi, 2013; Majhi *et al.,* 2020). It was revelead from literature that the meteorological data are only used to develop predictive models for hydrological and meteorological parameters. However, in time series analysis, meteorological parameters are stochastic in nature and repeated with static time-series such as Julian date. So, use of static time series as input variables might assist the neural network to learn the trend of meteorological parameters

Article info - DOI: *https://doi.org/10.54386/jam.v26i1.2247*
Received:9 June 2023; Accepted: 14 December 2023; Published online : 1 March 2024

to improve accuracy in prediction of evaporation rates. Therefore, present study was undertaken to evaluate the performance of soft computing techniques viz. ANN and LSTM for (E_{pan}) estimation using preceding 1-, 3-, and 5-days meteorological data. Besides this, the effect of static time-series Julian date (JD) as input variables were attempted to investigat the performance of ANN and LSTM models for estimation of daily pan evaporation.

MATERIALS AND METHODS

The daily meteorological data (maximum temperature, minimum temperature, morning relative humiditie, evening relative humidity, wind velocities, sunshine hours and rainfall) from 1984 to 2021 of IARI research farm, New Delhi, was collected from the Division of Agricultural Physics, ICAR-IARI, New Delhi. Initially, the data set contained some missing values. Thus, preprocessing of data was carried out for the accuracy of the model. The missing values were replaced with the mean values. Data scaling, normalization and transformation of data into a standardized form were undertaken. Normalization of data assisted to scale the data pertaining to an attribute so that it would be restricted to a smaller range between 0 to 1 or -1 to 1. The min-max normalization method was used using the formula as shown in Equation 1.

$$Y_{normalized} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad (1)$$

Where, $Y_{normalized}$ represents normalized data, Y is the actual value of data to be normalized, Y_{max} represents maximum value of data, Y_{min} represents minimum value of data, respectively.

Artificial neural network (ANN) architecture

ANN architecture consists of an input layer, intermediate layers (hidden layer) and an output layer. The hidden layers may be one or more depending on the data type and the model error statistics. Also, the number of nodes in the hidden layer plays a significant role in ANN model performance (Naresh *et al.,* 2023; Kumar *et al.,* 2022). There are no fixed rules for developing an ANN and a general framework was adopted based on previous successful applications in hydrology and agricultural water management. ANN trained with three numbers of hidden layers with a single output node was chosen as the criterion for the selection of optimal architecture. The general architecture of the ANN for estimation of pan evaporation is shown in Fig. 1.

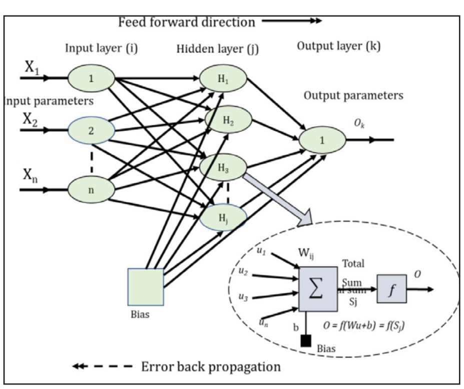

Fig. 1: Artificial neural network architecture

Each neuron has a number of input arcs connected (Fig. 1), u_1 to u_n, and associated with each i, there is a weight (W_{ij}), which representsa factor by which a value passing to the neuron is multiplied. A neuron sums the values of all inputs (S_j) as:

$$S_j = \sum W_u + b \quad (2)$$

In Fig. 1, W_u corresponds to the summation of weights W_{ij}. The term b is called bias. Finally, an activation function isn applied to to provide the final output from the neuron. The sigmoid function transform the continuous real number into a range of (0, 1), so that the input value of the next layer is within a fixed range and the weight is more stable (W_{ij}).The sigmoid function (φ) is given by

$$\varphi(S_j) = \frac{1}{1 + e^{-S_j}} \quad (3)$$

where, S_j is the value of the neuron at jth location.

LSTM model architecture

A specific architecture of deep Recurrent Neural Network (RNN) is Long-Short Term Memory (LSTM) network, which was an intended design for modelling temporal sequences (Kumar *et al.,* 2023). The basic structure of LSTM is known as a memory cell for remembering past event and predict future event using time-series datasets. A typical LSTM (Fig. 2) composed of two states which were the basic building blocks of a network, *i.e.,* cell state (C_t) and hidden state (h_t). Similarly, it has three gates such as 'forget' gate (f_t)- removing unwanted information from , c_t'input' gate (i_t)- adding new useful information to c_t in every time steps and 'output' gate h_t- updating c_t in each time step by incorporating information from the updated cell. These gates allow the LSTM to forget or memorize newly aquired information to the memory cell *i.e.* update c_t and h_t in every time step and the updated values of these two states are used to the next time step prediction (Majhi *et al.,* 2020). Collaborative performance of these gates enabled LSTM to work on time series data effectively.

In this study, ANN and LSTM were used as predictive model for one day ahead pan evaporation for two input senseiors as meteorological data and, meteorological data with Julian days ininput variables. Both models trained with three different input variables with preceding 1-day (LSTM-1 &ANN-1), 3-days (LSTM-3 & ANN-3), and 5-days (LSTM-5 & ANN-5), meteorological information. The available meteorological data were partitioned to

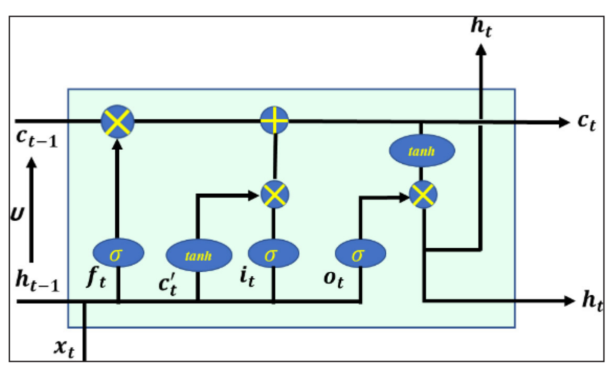

Fig. 2: Architecture of a long short-term memory (LSTM) network

three groups: training (60%), testing (20%), and validation (20%).

Model evaluation statistics

Statistical criteria, such as the mean absolute error (MAE), root mean square error (RMSE), Nash-Sutcliffe Efficiency (NSE), Kling–Gupta efficiency (KGE) and percent bias (PBias) were used as the prediction error statistics to ascertain the performance of the developed models.

$$\text{MAE} = = \frac{1}{n}\sum_{i=1}^{n}\left|x_{est_i} - x_{obs_i}\right| \quad (4)$$

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{est_i} - \overline{x_{est_i}}\right)^2} \quad (5)$$

$$\text{NSE}= 1- \frac{\sum_{i=1}^{n}\left(x_{est_i}-x_{obs_i}\right)^2}{\sum_{i=1}^{n}\left(x_{obs_i}-\overline{x_{obs}}\right)^2} \quad (6)$$

$$\text{KGE}= 1 - \sqrt{(1-r)^2+(\beta-1)^2+(\gamma-1)^2} \quad (7)$$

$$r = \frac{\sum_{i=1}^{n}\left(x_{obs_i}-\overline{x_{obs_i}}\right)\left(x_{est_i}-\overline{x_{est}}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_{obs_i}-x_{obs_i}\right)^2}\sqrt{\sum_{i=1}^{n}\left(x_{est_i}-\overline{x_{est}}\right)^2}} \quad (7a)$$

$$\beta = \overline{x_{est_i}}/\overline{x_{obs_i}}\ ;\ \gamma = \frac{\sigma_{est}/\overline{x_{est_i}}}{\sigma_{obs}/\overline{x_{obs_i}}} \quad (7b)$$

where, σ_{est} and σ_{obs} are the standard deviation of the estimated and observed E_{pan} , respectively.

$$\text{PBias} = \left[\sum_{i=1}^{n}\left(x_{est_i} - x_{obs_i}\right)/\sum_{i=1}^{n}x_{obs_i}\right] \times 100 \quad (8)$$

where n is the number of observations, x_{obs_i} and x_{est_i} are observed and predicted value, respectively, $\overline{x_{obs_i}}$ and $\overline{x_{est_i}}$ are the average values of observed and predicted data, respectively.

To select the optimum model input variables, the following criteria were considered to adjudge a model as excellent (0.75<NSE1; PBias<10; KGE 0.75), good (0.65<NSE0.75; PBias<15; 0.5≤ KGE < 0.75) and satisfactory (0.5<NSE0.65; PBias<25; 0.0 ≤ KGE < 0.5) (Commeh *et al.,* 2022; Thiemig *et al.,* 2013).

RESULTS AND DISCUSSION

Performances of ANN and LSTM Models

Daily pan evaporation *(Epan)* was estimated using preceding meteorological information by soft computing techniques of ANN and LSTM. Time-series ofthe observed and estimated *Epan* by using only meteorological data of preceding 1-, 3- and 5-daysis shown in Fig. 3. It was observed from Fig. 3 that both models simulated the trend of pan evaporation well for all three input variables during training, testing and validationprocesses. The ANN model indicated more stable and better performance than LSTM model for *Epan* estimation. In addition, it was found that the ANN models were able to capture the peak, intermediate as well as lowervalues while LSTM model had relatively poor performances in estimating lower *Epan* for all input scenarios (Fig. 3). Nonetheless, LSTM model trained with preceding 5- days meteorological data simulated the peak evaporation better than the other LSTM and ANN models (Fig. 3c). From the performance error statistics of LSTM and ANN models for *Epan* estimation using meteorological data are presented in Tables 1 and 2, respectively. It was found that the MAEs (mm) beween observed and estimated *Epan* were 0.71 to 0.95, 0.68 to 0.90 and 0.68 to 0.86 for ANN-1, ANN-3 and ANN-5, while 1.39 to 1.58, 0.98 to 1.20 and 1.12 to 1.27 for LSTM-1, LSTM-3 and LSTM-5, respectively. Besides this, the RMSEs were 0.98 to 1.36, 0.94 to 1.30 and 0.68 to 0.86 for ANN-1, ANN-3 and ANN-5, while 1.65 to 1.89, 1.18 to 1.53 and 0.93 to 1.22 for LSTM-1, LSTM-3 and LSTM-5, respectively. On the other hand, NSE (0.79 to 0.85) and KGE (0.87 to 0.92) were also higher for ANN than LSTM models (NSE: 0.42 to 0.78; KGE: 0.75 to 0.86). Moreover, the PBias of LSTM models (17.7 to 31.3) higher than ANN models (-7.7 to 2.4). Overall this indicated that the MAE<0.95 and RMSE<1.36 for ANN models were lower as compared to LSTM models (MAE>0.98 and RMSE>1.18) for all scenarios. Nonetheless, the ANN models exibited as excellent models (0.75<NSE1; PBias<10; KGE 0.75), while LSTM-1 exibited as satisfactory (0.5<NSE0.65; PBias<25; 0.0 ≤ KGE < 0.5), and for LSTM-3 and LSTMA-5 exibited as good (0.65<NSE0.75; PBias<15; 0.5≤ KGE < 0.75). LSTM models also showed high variability in performance error indictors, whereas the ANN models provided low variability in errors statistics. Moreover, the ANN models were observed to have the bestpredictive ability for daily *Epan* estimating for not only the lower values but also the peak values.

Form the performance error statistics Table 1 and 2, both LSTM and ANN model trained with using 3- or 5-days meteorological data exhibited better performance error statistics than models trained with only one day preceding meteorological data. It can be inferred that the time series estimation of meteorological parameters depends on preceding meteorological information.It was also observed that the LSTM model trained with preceding 3 days information performed at par with that of 5 days but better than preceding 1-day data (Table 1). Besides this, ANN models performance error statistics better trained with preceding 5-days meteorological data followed by 3- days and 1- day.

Effect of time-series input along with meteorological data on models' performance

An attempt was made to investigate the effect of static time-series (Julian date) as input variables along with meteorological data. Fig. 4 shows time-series of the observed and estimated *Epan* of LSTM and ANN models by using meteorological data along with Julian date for preceding 1-, 3- and 5- days information. The performance of LSTM models was improved for daily *Epan* simulation when static time series julian date added as input variables. This improvement was observed specially for LSTM models trained with preceding 3- and 5-days meteorological data (Fig. 4). Although LSTM overestimated the lower values, ANN models' performance was similar using only meteorological data to simulate the peak and lower values precisely.

Model performance error statistics indicated that the MAE (0.81 to 1.41), RMSE (0.84 to 1.68), PBias (5.15 to 15.07) were reduced and NSE (0.68 to 0.83) and KGE (0.76-0.90) increased for LSTMs trained with julian date as compared to use of only meteorological data (Table 1 and 3). However, ANNs performed well to simulate the peak and lower values (Fig. 4) as that of models trained with only meteorological data. Besides this, model performance error statistics also indicated that the performance was affected by using static time-series variables (Julian date) as input variables with meteorological data (Table 2 and 4). The MAE and RMSE were 0.66 to 0.89, and 0.92 to 1.29, respectively which

Table 1: Performance error statistics of LSTM using only meteorological data

LSTM models		MAE	RMSE	NSE	KGE	PBias
LSTM-1	Training	1.58	1.89	0.58	0.75	20.01
	Testing	1.39	1.66	0.64	0.79	17.52
	Validation	1.46	1.65	0.42	0.75	23.03
LSTM-3	Training	1.20	1.53	0.72	0.81	12.28
	Testing	1.02	1.29	0.78	0.86	9.96
	Validation	0.98	1.18	0.70	0.82	14.62
LSTM-5	Training	1.27	1.58	0.71	0.80	14.62
	Testing	1.12	1.39	0.75	0.83	12.80
	Validation	1.13	1.31	0.63	0.80	17.73

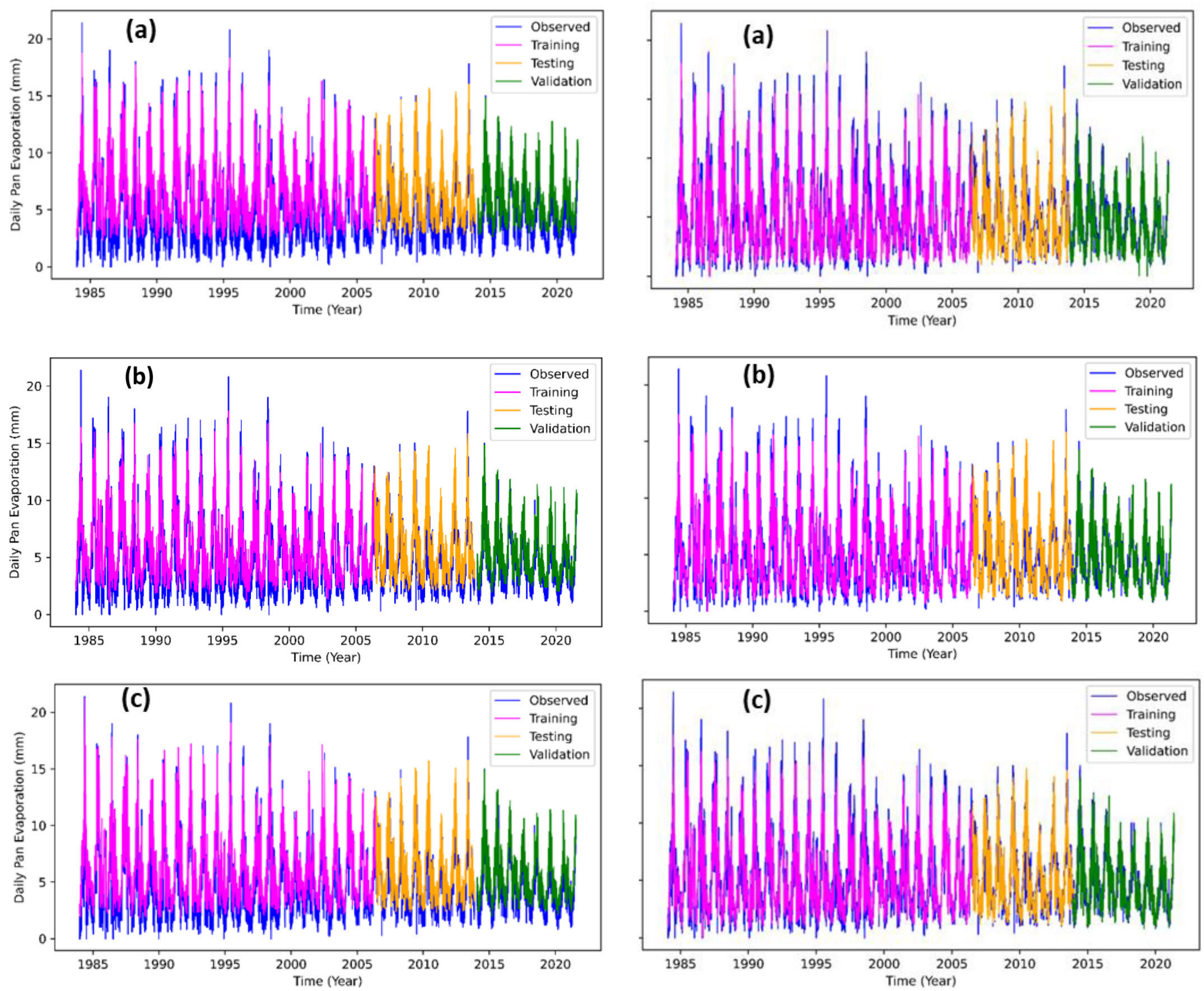

Fig. 3: Time series for observed and estimated *Epan* of LSTM & ANN using a) 1-day, b) 3-days and c) 5- days preceding meteorological information

was higher than models trained with only meteorological data. Also, NSE (0.79 to 0.84) and KGE (0.85 to 0.92) values were lower than models using only meteorological data.

It was observed that the LSTM and ANN have their own potential for time-series forecasting. The LSTM simulated peak pan evaporation precisely whereas overestimated for lower values.

Table 2: Performance error statistics of ANNs using only meteorological data

	ANN models	MAE	RMSE	NSE	KGE	PBias
ANN-1	Training	0.95	1.36	0.80	0.88	-3.52
	Testing	0.90	1.29	0.79	0.87	-7.66
	Validation	0.71	0.98	0.81	0.90	-4.22
ANN-3	Training	0.90	1.30	0.83	0.91	2.14
	Testing	0.82	1.16	0.85	0.92	-0.30
	Validation	0.68	0.94	0.85	0.90	2.15
ANN-5	Training	0.86	1.22	0.83	0.89	1.55
	Testing	0.80	1.14	0.83	0.90	-0.73
	Validation	0.68	0.93	0.84	0.92	2.44

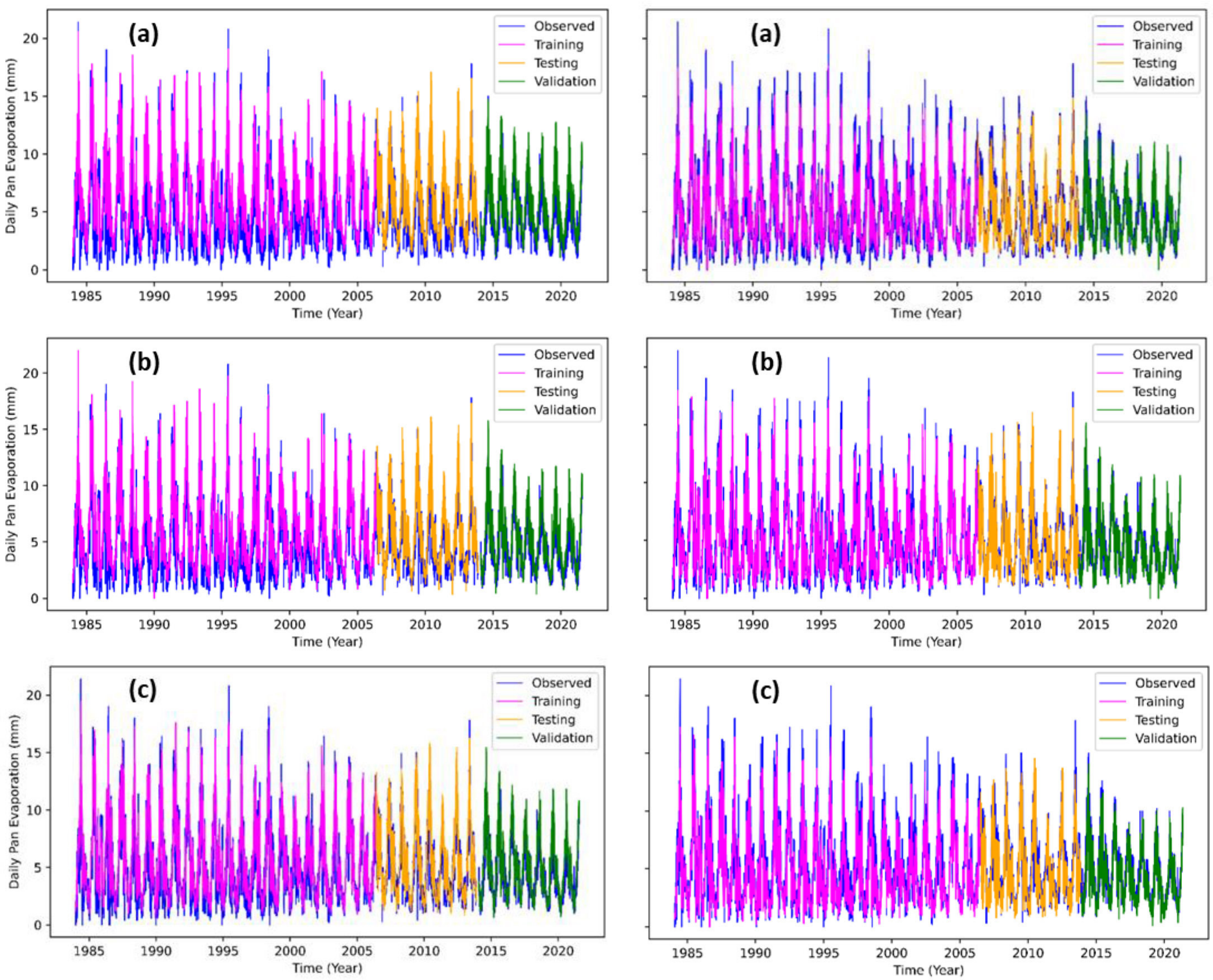

Fig. 4: Time series for observed and estimated *Epan* of LSTM & ANN using a) 1-day, b) 3-days and c) 5 days precedingmeteorological data with Julian date

LSTMs trained with preceding 3- and 5-days meteorological data performed better than the preceding 1-day information (Figs. 3 and 4). However, LSTM with preceding 3 days information simulated the peak and lower values over 5 days (Figs. 3 and 4) more accurately than using the one day data. While, performance error statistics of LSTM models trained with preceding 5-days meteorological and

Table 3: Performance error statistics of LSTMs using meteorological data with Julian dates

LSTM models		MAE	RMSE	NSE	KGE	PBIAS
LSTM-1	Training	1.27	1.68	0.73	0.82	15.07
	Testing	1.07	1.45	0.78	0.84	12.51
	Validation	1.17	1.48	0.68	0.76	18.52
LSTM-3	Training	1.08	1.47	0.79	0.86	11.63
	Testing	0.90	1.24	0.83	0.88	8.55
	Validation	0.87	1.15	0.79	0.83	12.50
LSTM-5	Training	0.99	1.39	0.81	0.88	8.16
	Testing	1.41	0.84	0.85	0.90	5.14
	Validation	0.81	1.11	0.82	0.83	9.94

Table 4: Performance error statistics of ANNs using meteorological data with Julian dates

ANN models		MAE	RMSE	NSE	KGE	PBIAS
ANN-1	Training	0.89	1.29	0.80	0.85	-2.95
	Testing	0.88	1.25	0.79	0.86	-8.02
	Validation	0.70	0.94	0.83	0.91	-2.60
ANN-3	Training	0.86	1.23	0.84	0.92	0.01
	Testing	0.84	1.21	0.83	0.91	-1.86
	Validation	0.66	0.92	0.84	0.92	-0.51
ANN-5	Training	0.88	1.25	0.82	0.87	-6.12
	Testing	0.87	1.24	0.79	0.86	-8.15
	Validation	0.66	0.92	0.83	0.89	-5.53

julian date was observed to be the best (0.75<NSE1; PBias<10; KGE 0.75) with MAE<1.41 mm and RMSE<1.39 mm as compared to other LSTM models (Tables 1 and 3).Moreover, ANNs performed better than the LSTM to simulate peak as well lower pan evaporation with marginal underestimated and overestimated the peak and lower values for all seneraios (Figs. 3 and 4). The performance error ststitics of ANNs using preceding 1-, 3- and 5- days' meteorological information were in line with each others. However, ANN with preceding 5- days information had a little edge over 3- days followed by 1-day preceding information (Tables 2 and 4). The use of static time-series variables in input along with meteorological parameters affected the simulation as well performance error statistics of LSTMs whereas the performance of ANNs was stable (Figs. 3 and 4; Table 1 to 4). Further, the use of Julian date in input along with preceding 5-days information improved the LSTMs performance (0.75<NSE1; PBias<10; KGE 0.75). Besides this, ANN's performance did not improve much by using julian date in input variables. Thus, the ANN trained with using only preceding 5- days meteorological data performed better which can be used for daily *Epan* estimation for irrigation scheduling and efficient water resource management.

Overall, the performance error statistics of LSTMs and ANNs model evaluated for different sceanearios indicated that the LSTM-3 estimated *Epan* better than LSTM-5 followed by LSTM-1 when the model trained with only metreorological data, while the performance of LSTM-5 was better than LSTM-3 and LSTM-1, by using the metreorological data and Julian date. On the other hand, performance of ANN-5 was better than ANN-3 followed by ANN-1 for all scenarios. Besides this, the use of Julian date as input variable improved the performance of LSTMs. The improve in performance by using Julian date as input may be due to representing the entire year leading to adequate learning of the soft computing tools. Therefore, it can be concluded that estimation of meteorological parameters requires a few days preceding information for better testing and learning of these tools. So the use of static time series variable as julian date could improve the predictability of soft computing techniques.

CONCLUSION

In the present study evaluated the performance of soft computing techniques *viz.* LSTM and ANN for daily pan evaporation estimation, which were trained with 1-, 3- and 5- days preceding meteorologicaldata and, along with static time series (Julian date) as input variable. It was LSTMs simulated peak pan evaporation precisely with observed values but overestimated lower values. While, ANNs simulated peak as well lower pan evaporation values with marginal under and over-estimated with preceding 5- days meteorological information followed by 3- days and 1- day, respectivelt. The models trained with meteorological data and julian date improve the performance error statistics of LSTMs, however the performance error statistics of ANNs like the used only meteorological data. The ANN trained with using only meteorological data (5 days preceding information) had better performance error statistics among all others ANNs and LSTMs with minimum MAE, RMSE, PBias; and maximum NSE and KGE. Therefore, the results of the proposed ANN-5 model can be used for *Epan* estimation.

ACKNOWLEDGEMENT

Authors are thankful to the Director, ICAR-IARI, New Delhi, and the Head, Division of Agricultural Physics, ICAR-IARI, New Delhi for providing the necessary facilities and meteorological data for carrying out the research work.

***Data availability*:** The authors do not have permission to share data.

***Competing Interest*:** The authors declare that they have no competing interest.

***Funding*:** The authors did not receive support from any organization for the submitted work.

Author's contributions **:Kumar, Sarangi and Singh**: Conceptualization, Methodology; **Kumar, Dash and Bandhyopadhyay**: Analysis, Visualization; **Kumar and Sarangi**: Investigation, Writing-original draft; **Mani, Khanna and Sarangi**: Writing-review and editing; **Sarangi:** Supervision.

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