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Hybrid Approaches for Irrigation Optimization Based on Weather Forecast: a Study on Reference Evapotranspiration Prediction in Beni Mellal

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Abstract

Accurate prediction of Reference Evapotranspiration (ET0) is vital for optimizing irrigation, thereby facilitating efficient water management and agricultural planning. This study compares three distinct methods for predicting ET0 using the FAO Penman-Monteith (FAO-PM), leveraging daily weather data collected over a span of 38 years, from 1984 to 2022. The first approach involves predicting ET0 directly based on actual ET0 values, while the second hybrid approach uses Recurrent Neural Networks (RNN) to predict Net Radiation, Temperature, Wind speed, and Dew Point Temperature. These predicted values are then utilized in the FAO-PM equation to calculate ET0 (RNN-FAO-PM). The third approach is another hybrid method that combines RNN for predicting the weather parameters, followed by the application of a well-trained Random Forest (RF) model that uses the predicted weather parameters as features to predict ET0 (RNN-RF). The performance of each method is evaluated using various metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R2) values for both training and testing datasets. The results of this study reveal that the hybrid approaches demonstrate comparable performance for long-term prediction of ET0 of the period Spanning from 2020 to 2022 (3 years). These hybrid approaches slightly outperform the RNN method when applied solely on the ET0 time series. This finding contributes to the research in the area of water resource management, specifically in the context of irrigation optimization. It provides valuable insights that can inform agricultural decision-making in the Beni Mellal region, enabling more efficient and effective use of water resources for irrigation purposes..

Keywords

Reference evapotranspiration forecast, irrigation optimization, deep learning, weather forecast.

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Introduction

Optimizing irrigation is crucial in agriculture for enhancing crop yield, conserving water, and minimizing environmental impacts. Especially in the region of Beni Mellal, where agriculture is the main source of income, in addition to the region having unprecedented consecutive years of insufficient rainfall. This has significantly affected the water levels in the dams, making it crucial to have a clear vision of long-term variations and anticipate on daily basis the required water for proper irrigation. ET0 plays a central role in determining the appropriate water application and timing of irrigation sessions. ET0 holds paramount significance as it stands as a crucial input in various methods. Indeed, it is the central component and playing a vital role in optimizing irrigation management (Liu and Yang, 2021), ET0 serves as the foundation for calculating Crop Evapotranspiration (ETc), a key component in the soil water balance equation (Hou et al., 2022) (Mininnia et al. 2022), water budget (Das et al., 2023), a reference point for plant indicators (Livellara et al., 2011), and decision support systems (DSS) (Olberz et al., 2018) (Khatua and Pasupalak, 2018). Understanding and utilizing ET0 can improve water use efficiency, reduce waste, and enhance crop productivity. The importance of ET0 in irrigation management cannot be overstated, and it is essential for farmers and researchers to continue exploring new ways to utilize ET0 to improve irrigation practices. This study aims to compare three methods for predicting ET0 with the goal of identifying the most effective method. The methods under investigation are: Direct prediction of ET0 from actual ET0 values using RNN, Hybrid RNN-FAO-PM and Hybrid RNN-RF.

This following literature review highlights the significance of ET0 estimation and explores the potential of machine learning techniques in studying ET0 patterns. It discusses specific methods for different implementations, and the effectiveness of hybrid models and simplified determination approaches. In the following study (Yildirim et al., 2023), the authors employ machine learning methods, including the k-nearest neighbor algorithm, multigene genetic programming, and support vector regression (SVR), to predict daily ET0 in various regions, including Türkiye. In another study (Ling et al., 2023) the authors focus on rubber plantations and propose the "Kc-ET0" method, which demonstrates good performance and acceptable precision, particularly in the dry season. The authors of a separate study (Zheng et al., 2023) suggest a strategy based on Multivariate Variational Mode Decomposition hybridized with Soft Feature Filter and Gated Recurrent Unit (GRU) to predict one-day daily ET0. This strategy outperforms other models such as Long Short-Term Memory (LSTM), BiLSTM, RNN, BiRNN, and BiGRU, proving to be the most accurate for predicting one-day ahead ET0. In the realm of sustainable agricultural development, the authors (Bashir et al., 2023) highlight the importance of ET0 for the preservation of irrigation water. They suggest machine learning approaches to simplify ET0 determination with limited parameters, achieving high precision and correlation with the FAO-56 Penman-Monteith (FAO-56 PM) method. The precision of ET0 estimated by reanalysis products, such as CLDAS and ERA5, is evaluated in another study (Yu et al., 2023). These products demonstrate acceptable precision in China, with CLDAS estimates showing higher spatial and temporal consistency with site observations. In Egypt, where climates range from arid to semi-arid and there are challenges related to a lack of meteorological data and future information on ET0. The authors (Elbeltagi et al., 2023) investigate the use of machine learning models such as linear regression (LR), random subspace (RSS), additive regression (AR), and reduced error pruning tree (REPTree) to precisely estimate ET0. Among these models, REPTree demonstrates the best performance. The authors of a different study (Saggi et al., 2023) explore various machine learning models, including Extreme Machine Learning (ELM), Multi-layer Perceptrons-Neural Network (MLP), and Support Vector Machine (SVM), for modeling daily ET0. An ensemble method with SVM demonstrates good precision in predicting the daily ET0. Addressing the challenges faced by irrigation district managers. The authors (González Perea et al., 2023) develop a hybrid model combining Fuzzy Logic (FL), Genetic Algorithm (GA), LSTM encoder-decoder, and dense or fully connected neural networks (DNN) for the one-week forecasting of irrigation water demand at the irrigation district scale. The potential of ET0 as a key variable for irrigation management, agricultural planning, and modeling different hydrological processes is emphasized in another study (Adnan et al., 2020), the authors validate temperature-based heuristic models such as group method of data handling neural network (GMDHNN), multivariate adaptive regression spline (MARS), and M5 model tree (M5Tree) for estimating monthly ET0. Among these models, the GMDHNN model provides the best accuracy. In regard of This research (Amirashayeri et al., 2023) it focus on accurately predicting ET0 using machine learning models and empirical equations. The study compares the performance of an artificial neural network (ANN) model and a tree model (MT) with two empirical equations. Additionally, a preprocessing algorithm called ensemble empirical mode decomposition (EEMD) is used to enhance the prediction accuracy of the MT model and eliminate time-series noises. The results show that the MT model outperforms the ANN model, and the incorporation of EEMD significantly improves the MT model's performance. Overall, this research highlights the potential of machine learning models and the EEMD algorithm in accurately predicting ET0, which has important implications for managing agricultural water needs and irrigation systems. Based on the analysis of various studies, including the one included in the literature review, it is evident that there is a lack of long-term prediction of ET0 with various combinations. In order to address this gap, we propose three methods. The first method utilizes a forecasting technique based on the temporal dependencies of the ET0 time series using RNN. By considering the historical patterns and trends in the ET0 data, the RNN model can make predictions for future time periods. The second method involves a hybrid model that combines the impractical equation FAO-PM method with RNN. By integrating this equation with RNN, which can capture the temporal dependencies, we can enhance the accuracy of long-term ET0 predictions. The third method combines RNN with RF, another machine learning algorithm known for its ability to handle complex datasets. By leveraging the strengths of both RNN and RF, we can further improve the accuracy and robustness of long-term ET0 predictions. These three methods aim to address the lack of long-term ET0 prediction by utilizing different approaches and models, considering temporal dependencies, integrating practical equations, and leveraging the power of machine learning algorithms to provide more accurate and reliable predictions for ET0 in various combinations.

Materials and methods

The FAO-PM method is widely recognized as the standard approach for estimating ET0 backed by the Food and Agriculture Organization of the United Nations as the sole method for determining ET0 (Allen et al. 2000; Allen, 1977). The ET0 formula refines the original Penman-Monteith equation, incorporating aerodynamic and surface resistance for accurate evapotranspiration estimation. The equation (1) is:

$$ET0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

Where:

ET0: Reference Evapotranspiration [mm day-1].

Rn: net radiation at the crop surface [MJ m-2 day-1].

G: soil heat flux density [MJ m-2 day-1].

T: air temperature at 2 m height [°C].

u2: wind speed at 2 m height [m s-1].

es: saturation vapour pressure [kPa].

ea: actual vapour pressure [kPa].

es-ea: saturation vapour pressure deficit [kPa].

Δ: slope vapour pressure curve [kPa °C-1].

γ: psychrometric constant [kPa °C-1], the psychrometric constant is rounded to 0.067 kPa/°C.

Because of it efficiency to approximate grass ET0 at various locations, in addition to accounting for various meteorological parameters, such as Net Radiation, Temperature, Wind speed, and Dew Point Temperature. in addition to various studies whom Backed-up it efficiency (Jayashree et al., 2023; Eliades et al., 2022). To estimate ET0 using the FAO-PM method, we utilized four weather parameters: all-sky surface shortwave upward irradiance and the all-sky surface shortwave downward irradiance [MJ m-2 day-1], mean Temperature at 2 meters above the ground [°C], Dew Point Temperature [°C], and Wind speed at 2 meters height [m s-1]. These parameters are obtained from Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). The FAO-PM method requires several calculations, such as determining the slope of the saturation vapor pressure curve (Δ) and the actual vapor pressure (ea) and Mean saturation vapour pressure (es) using temperature-dependent equations. The actual vapor pressure is calculated based on the Dew Point Temperature. given by (Equation 2):

$$e_a = 0.6108\exp\left[\frac{17.27\, T_{dew}}{T_{dew} + 237.3}\right] \quad (2)$$

The saturation vapor pressure is intricately tied to the air temperature, and its calculation is elucidated by the following relationship (Equation 3):

$$e_s = 0.6108\exp\left[\frac{17.27\, T}{T + 237.3}\right] \quad (3)$$

In regard to the slope of saturation vapor pressure curve (Δ) is computed using Temperature data (Equation 4):

$$\Delta = \frac{4098\left[0.6108\exp\left(\frac{17.27\, T}{T + 237.3}\right)\right]}{(T + 237.3)^2} \quad (4)$$

Where

Δ: slope of saturation vapour pressure curve at air temperature T [kPa °C-1].

T: air temperature [°C].

exp[]: base of natural logarithm.

Net radiation is derived by subtracting the all-sky surface shortwave upward irradiance from the all-sky surface shortwave downward irradiance. For daily ET0 calculations, the soil heat flux is considered zero, as its impact on the daily ET0 is negligible compared to Net Radiation and other energy fluxes.

We develop predictive RNNs models using historical daily values from January 1, 1984 to November 30, 2022 in total 14213 records this time series is split as the following sets: 12792 records for training (90%), 1421 records for testing (10%) in addiction to conserving 10% of the training set to make a validation set. The data is further prepared for the LSTM model using the look-back period of 8. Upon performing a grid search to determine optimal parameters the LSTM and GRU models were implemented with identical parameter settings due to their similar response patterns to any changes in parameters, resulting in either improvement or deterioration of the models. The RNN model is then created using the Sequential API. The RNN model consists of either a GRU or LSTM layer with 256 units, followed by a Dense layer with 64 units, and finally a Dense layer with a single unit. The activation function used is ReLU. The model is compiled using the Adam optimizer with a learning rate of 0.001 was utilized in conjunction with the learning rate scheduler. Moreover, the loss function is MSE. The model is then trained using a batch size of 64 and a validation split of 0.1. The training is performed for 20000 epochs, with the model checkpoint as a callback. A model checkpoint is created to save the model after each epoch, the 20000 models are saved then base on the validation loss values the best model is applied on the time series. The meteorological parameters are namely Net Radiation, Temperature, Dew point, Wind speed collected from MERRA-2, And the daily-calculated ET0 values are based on the FAO-PM approach.

The first method, consist of directly predicting of ET0 from actual ET0 values, this method being the simplest and most straightforward. It involves around simply predicting ET0 directly from actual ET0 values. This is done using two RNN namely GRU and LSTM. We shall compare the result using three metric namely MAE, RMSE and R2.

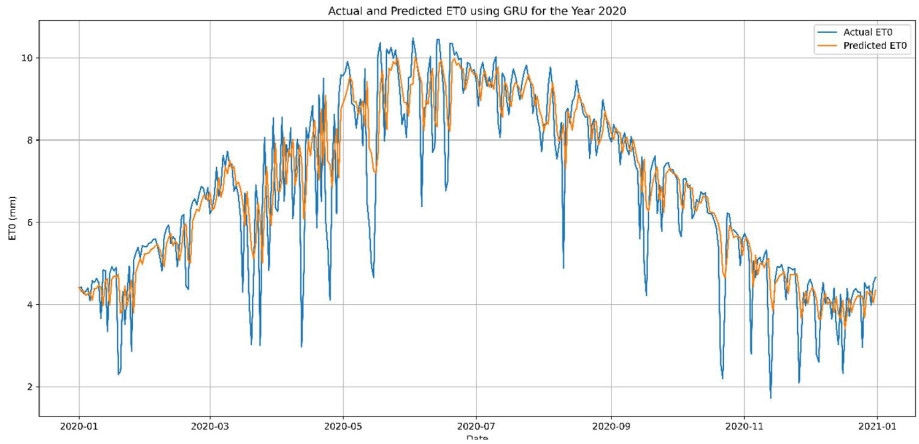
The second method, the hybrid RNN- FAO-PM method, this method first involves predicting individual weather parameters required for the FAO-PM method using both GRU and LSTM models. The weather parameters to be predicted include Net Radiation, air temperature, dew point temperature, and wind speed. Based on the performance metrics of MAE, RMSE, and R2, the best prediction model between GRU and LSTM is selected for each weather parameter. After choosing the best RNN algorithm from the two, the predicted weather parameters are then used to calculate ET0 using the FAO-PM method.

The third method, we employed a RF regression model to predict ET0 using the predicted four weather parameters as features namely Net Radiation, Temperature, Wind speed, and Dew Point Temperature. To evaluate the RF model's performance during training and estimate its ability to generalize to new data, we used Time Series Cross-Validation with 5 folds. In this approach, the training set is divided into 5 contiguous blocks, and the model is trained and evaluated 5 times, with each block being used for testing and validation. The average MAE across all five iterations is used to assess the model's performance during training. After the RF model proved it efficacy, we supplemented it with the predicted weather parameters from RNN. This combined RNN-RF approach aimed to leverage the strengths of combined models, with the RNN capturing complex temporal patterns in the weather data and the RF model providing ET0 predictions based on the predicted weather parameters acting as features

Results and discussion

Weather forecasting using deep learning algorithms

The first method is the most straight forward, two deep learning algorithms GRU and LSTM, were employed to predict ET0. The performance of these models is evaluated using three metrics: MAE, RMSE, and R2. Table 1 presents a comparison based on the values obtained from the best parameters found during a three-year prediction period spanning from 2020 to 2022. Comparing the performance of the two RNNs models, The GRU model appears to be more effective in predicting the component of the water cycle ET0 compared to the LSTM model, as evidenced by the lower MAE and RMSE for both the training and testing datasets and higher R2 values. The Figure 1 illustrates the comparison between the actual and predicted ET0 values for the entire year of 2020. The x-axis represents the ET0 values in millimeters per day, while the y-axis represents the time period, ranging from January to December. The overall trend of the predicted values closely follows the actual ET0 values, it is clear that the predicted values do not demonstrate a similar level of decrease during periods characterized by sudden drops in ET0.



Source: Author's illustration

Figure 1: Comparison of actual and predicted ET0 values for the year 2020 using GRU.

Component of the water cycle	Deep learning algorithm	Number of epochs	MAE		RMSE		R2	
			Training	Testing	Training	Testing	Training	Testing
ET0	GRU	24	0.7247	0.6937	1.0953	1.0403	0.7536	0.7649
	LSTM	29	0.7254	0.6958	1.1030	1.0532	0.7501	0.7609

Source: Authors

Table 1: Evaluation of GRU and LSTM models for ET0 prediction period spanning from 2021 to 2022.

Hybrid approaches

Weather Forecasting Using Deep Learning Algorithms

In the pursuit of accurate ET0 prediction, two hybrid approaches were developed. The RNN-FAO-PM, is designed to forecast the weather parameters then calculation ET0 using the FAO-PM method. The RNN-RF employs a RF model to predict ET0, utilizing as features the following Net Radiation, Temperature, Wind speed, and Dew Point Temperature. To provide reliable input for these approaches, weather parameters are predicted using two deep learning algorithms: GRU and LSTM. The performance of these models is evaluated using MAE, RMSE, R2 values for both training and testing datasets the results are shared in Table 2.

The analysis of the predicted four weather using deep learning algorithms GRU and LSTM, reveals several key insights. The prediction of Net Radiation, as depicted in Figure 2, is quite satisfactory. The overall trend of the predicted values closely mirrors the actual values, demonstrating the model's ability to capture the general patterns of Net Radiation. However, during periods of sudden drops in Net Radiation, the predicted values do not exhibit the same magnitude of decrease as the actual values. This discrepancy suggests that the model may struggle to accurately capture extreme fluctuations in Net Radiation, a limitation that warrants further investigation. The prediction of Temperature, on the other hand, is exceptional. Both GRU and LSTM algorithms yield low MAE and RMSE values for both training and testing, indicating a high degree of accuracy in predicting Temperature. Figure 3, which illustrates the Temperature predictions, further corroborates this observation by showing a close alignment between the predicted and actual values. The prediction of Wind speed, as shown in Figure 4, is generally good as it follows the main patterns. However, the model's performance diminishes when it comes to accurately predicting extreme highs and lows in Wind speed. This is evident from the higher MAE and RMSE values for Wind speed compared to Temperature, indicating a higher degree of error in these predictions. The prediction of Dew Point Temperature, represented in Figure 5, is also good, albeit not as accurate as Temperature. The MAE and RMSE values for Dew Point Temperature are slightly higher compared to Temperature, indicating that the models had slightly higher errors in predicting Dew Point Temperature. However, the models still exhibited relatively low errors, suggesting that they were able to capture the overall patterns and variations in Dew Point Temperature.

Weather parameter	Deep learning algorithm	Number of epochs	MAE		RMSE		R2	
			Training	Testing	Training	Testing	Training	Testing
Net Radiation	GRU	29	0.4948	**0.4710**	0.7547	**0.7134**	0.7469	**0.7625**
	LSTM	30	0.4934	0.4722	0.7528	0.7165	0.7481	0.7605
Temperature	GRU	70	1.2296	**1.2639**	1.6065	**1.6440**	0.9559	**0.9533**
	LSTM	67	1.2341	1.2695	1.6053	1.6473	0.9559	0.9531
Wind speed	GRU	61	0.2648	**0.2511**	0.3919	**0.3533**	0.3426	**0.3594**
	LSTM	32	0.2671	**0.2511**	0.3979	0.3555	0.3225	0.3516
Dew Point Temperature	GRU	81	1.6368	**1.5913**	2.1243	**2.1097**	0.7362	**0.7610**
	LSTM	55	1.6357	1.5935	2.1271	2.1123	0.7355	0.7604

Source: Authors

Table 2: Performance evaluation of GRU and LSTM models for weather parameter prediction in the period spanning from 2021 to 2022.

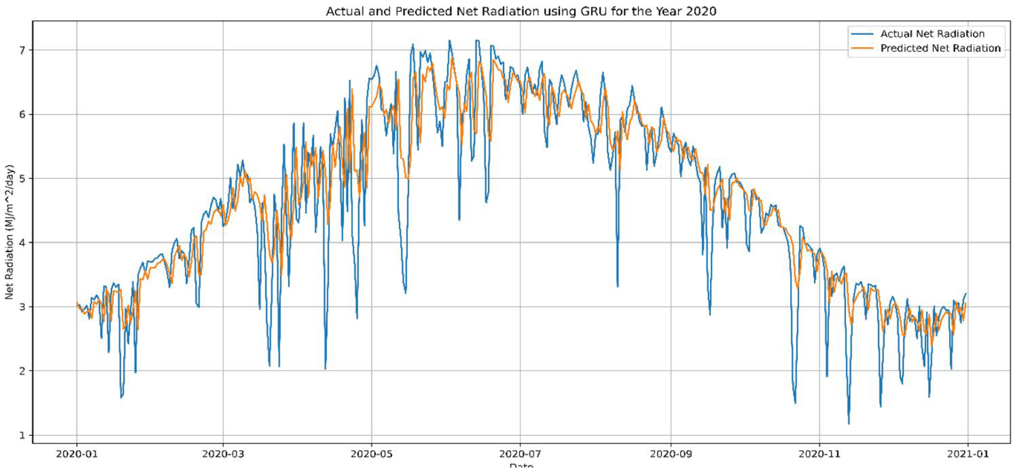


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Figure 2: Comparison of actual and predicted net radiation values for the year 2020 using GRU.

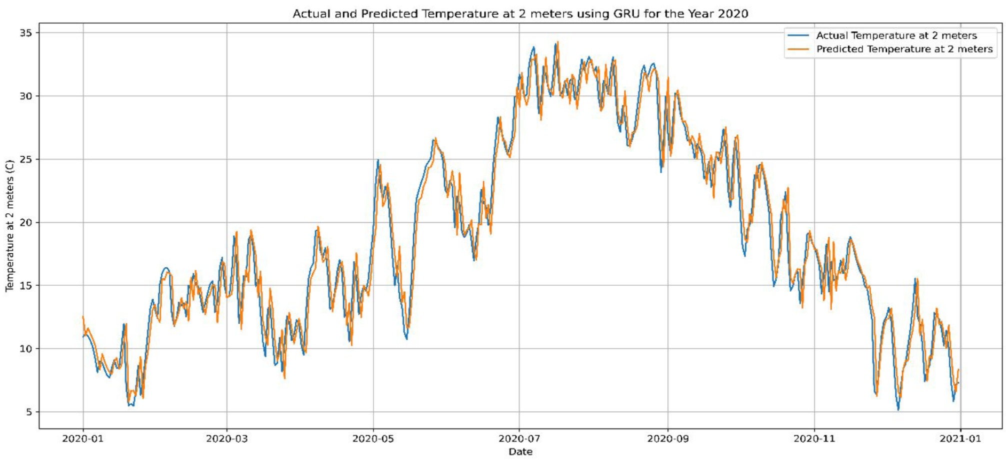

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Figure 3: Comparison of actual and predicted temperature values for the year 2020 using GRU.

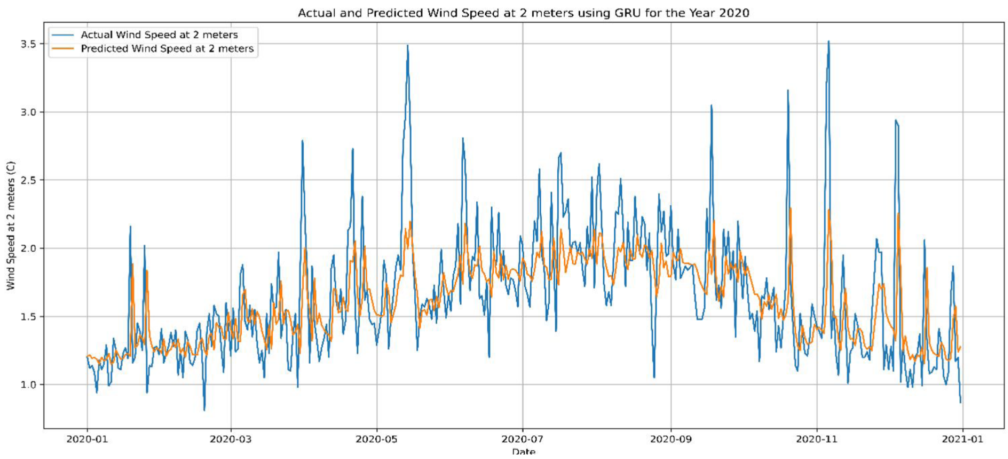

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Figure 4: Comparison of actual and predicted wind speed values for the year 2020 using GRU.

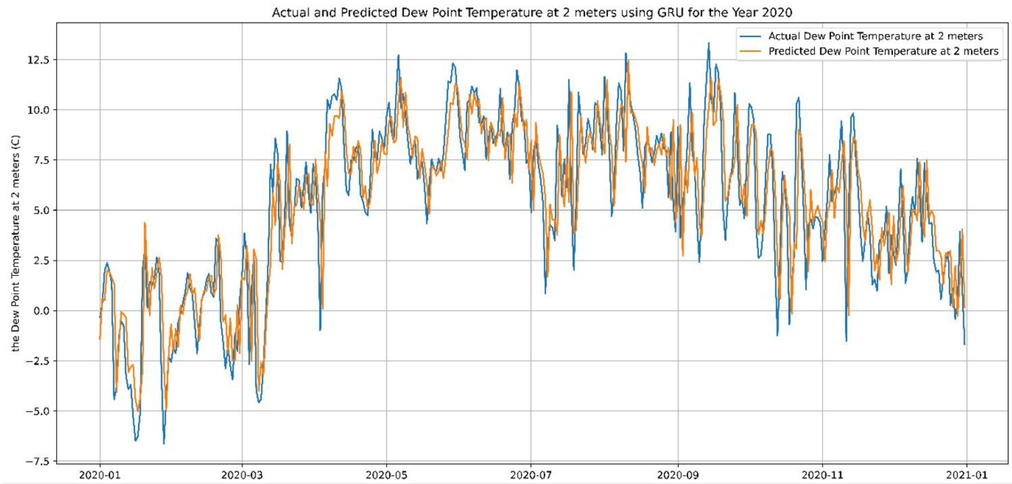

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Figure 5: Comparison of actual and predicted dew point temperature values for the year 2020 using GRU.

The hybrid model: using Deep Learning-based prediction of weather parameters to calculate ET0 using the FAO-PM method (GRU-FAO-PM)

After choosing the best RNN algorithm for each individual weather parameter, the predicted weather parameters were used as input to calculate ET0 using the FAO-PM method. The MAE and RMSE, R2 values indicated in Table 3 obtained when comparing actual ET0 vs predicted ET0 for the Period Spanning from 2020 to 2022. The MAE of 0.6873 and RMSE of 1.0422 demonstrate a reasonably accurate prediction of ET0 and the same remark persists the ET0 values are not well predicted in cases of sudden drops. Refer to Figure 6 for a comparison of actual and predicted ET0 using GRU-FAO-PM.

	Model	MAE	RMSE	R2
ET0 (in mm)	GRU-FAO--PM	0.6873	1.0422	0.7640

Source: Authors

Table 3: Performance metrics of a Hybrid Deep Learning-Based Approach for ET0 prediction using the FAO-PM method for the period spanning from 2020 to 2022.

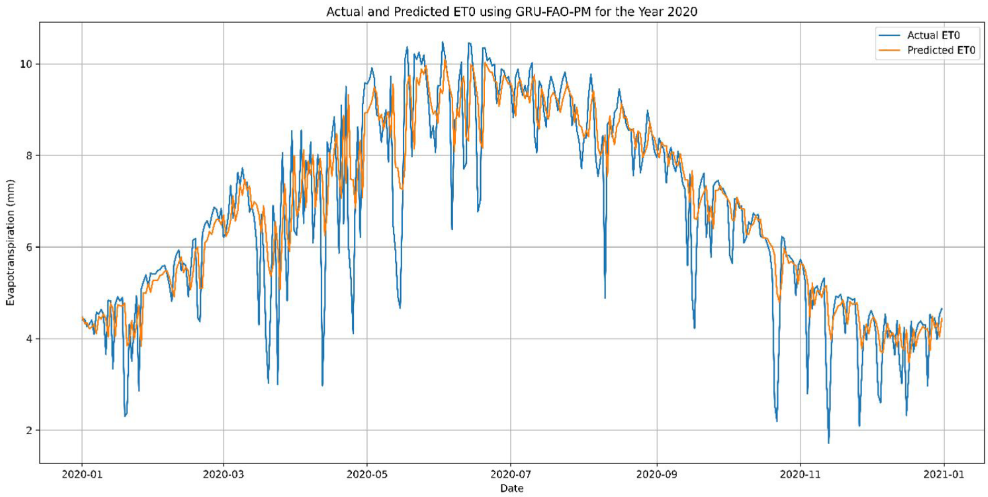

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Figure 6. Comparison of actual and predicted ET0 values for the year 2020 using GRU-FAO-PM.

The Hybrid model: RF based prediction of ET0 from predicted weather parameters using GRU (GRU-RF)

A two-step approach is employed to predict ET0 using weather parameters. First, the RNN models is used to predict weather parameters: Net Radiation, Temperature, Wind speed, and Dew Point Temperature using GRU. These predicted weather parameters were then used as input features for a RF regression model to predict ET0. The model's performance on both the testing and validation sets is consistently strong across all metrics as shown in Table 4, which is a good indication that it is not overfitting and can generalize well to new data. Additionally, the use of Time Series Cross-Validation with 5 folds during training helps to ensure that the model is robust and can handle different time periods in the data.

The performance of the combined GRU-RF model in predicting ET0 is assessed using various metrics indicated in The Table 5. With a MAE of 0.6873, the model's predictions, on average, deviate from the actual ET0 values by a relatively small margin. This highlights the overall accuracy of the model. Furthermore, the R2 value of 0.7642 indicates that the model can explain approximately 76.42% of the variance in the actual ET0 data, suggesting a reasonably good fit to the data and the model's ability to capture a significant portion of the underlying patterns in ET0. These results show that the model is effective in predicting ET0 and has potential for further optimization and improvement. Refer to Figure 7 for a comparison of actual and predicted ET0 using GRU-RF.

Features	Label	MAE		RMSE		R2	
		Tes-ting	Vali-dation	Tes-ting	Vali-dation	Tes-ting	Vali-dation
Net Radiation, Temperature, Wind speed, Temperature	ET0	0.0069	0.0063	0.0114	0.0093	0.9999	0.9999

Source: Authors

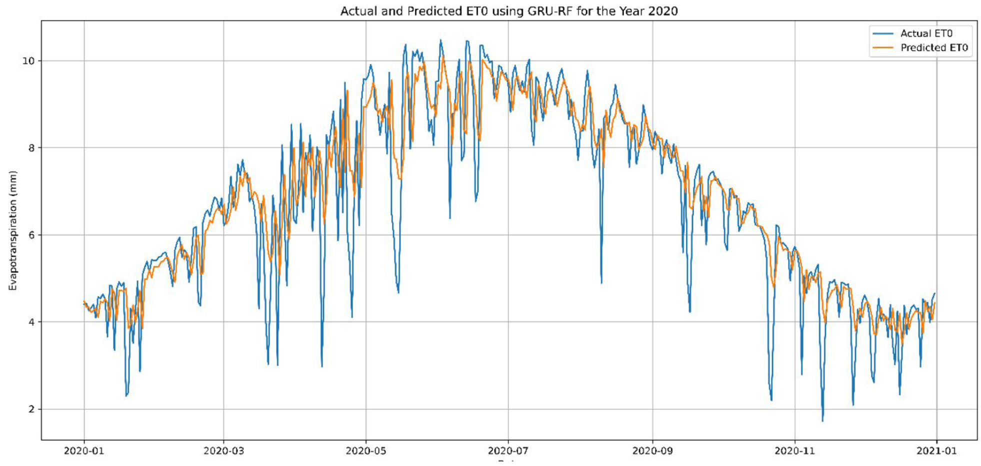
Table 4: Performance metrics of RF regression Mmdel for ET0 prediction using predicted RNN model as features for the period spanning from 2020 to 2022.

	Model	MAE	RMSE	R2
ET0 (in mm)	GRU-RF	0.6873	1.0418	0.7642

Source: Authors

Table 5. Performance metrics of hybrid random RF-based prediction of ET0 from predicted weather parameters using GRU.

Having the same MAE, RMSE, and R2 values indicates that both hybrid approaches are equally effective in predicting ET0. This suggests that the use of RNN for predicting weather parameters, followed by either the FAO-PM equation or a RF model, yields comparable results. There are several reasons why both approaches yielded similar MAE, RMSE, and R2 values. Firstly, the RNN used for weather prediction proved to be effective, providing reliable inputs for subsequent steps. The RNN's architecture and training process allowed it to accurately model the sequential nature of weather data. Secondly, both the FAO-PM equation and the RF model are well-established and robust methods for estimating ET0 when provided with relevant input parameters. The accurate weather predictions from the RNN



Source: Author's illustration

Figure 7: Comparison of actual and predicted ET0 values for the year 2020 using GRU-RF.

served as valuable inputs for leveraging the strengths of these models. Thirdly, the datasets used for training and evaluation contained sufficient and representative data, enabling both approaches to learn the underlying patterns and relationships effectively. This facilitated good generalization to unseen data. Lastly, its important to keep in mind while the evaluation metrics (MAE, RMSE, R2) provide an overall assessment of model performance, they may not capture subtle differences in prediction distributions or localized errors and biases.

Conclusion

This paper explore three methods for predicting ET0 over a period of three years. The methods included using a GRU model, a hybrid model combining RF with GRU (GRU-RF), and another hybrid model combining deep learning-based weather parameter prediction with the FAO-PM method (GRU-FAO-PM). The results of the study indicated that the GRU model performed well in predicting net radiation, although it struggled in cases of sudden drops in values. On the other hand, temperature and Dew Point Temperature predictions were found to be accurate. Wind Speed prediction, while relatively good, was identified as the weakest. In terms of predicting ET0, all three methods showed good overall performance. However, similar to Net Radiation, they faced challenges in accurately predicting values during sudden drops. Notably, the hybrid approaches GRU-RF and GRU-FAO-PM demonstrated better performance compared to the standalone GRU model, with similar MAE and RMSE values. In future work, we will explore several avenues in order to further improve the prediction accuracy of ET0 and address the challenges associated with predicting sudden drops in values, particularly for Net Radiation. One potential direction is to investigate alternative algorithms that may offer better performance in capturing these fluctuations such the Transformer-based models that leverages self-attention to capture the complex temporal dynamics in the time series through using Temporal Fusion Transformer mode

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