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Enhancing Estimation Of Evapotranspiration In Sugarcane Cultivation Using Lysimeter Data And Deep Learning Techniques

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Abstract: Accurate estimation of evapotranspiration (ET) is pivotal for optimizing water management in sugarcane cultivation. This study leverages lysimeter measurements combined with deep learning techniques to enhance the prediction accuracy of ET in sugarcane fields. Over a full growing season, high-resolution data were collected using precision lysimeters alongside meteorological parameters such as temperature, humidity, solar radiation, and wind speed. Two deep learning models, the Long Short-Term Memory (LSTM) network and the Convolutional Neural Network (CNN), were developed to model the complex relationships between environmental factors and ET rates. Model performance was evaluated using metrics like Mean Absolute Error (MAE) and the coefficient of determination (R^2). Results demonstrated that the LSTM model achieved superior performance, with an MAE of X mm/day and an R^2 of Y, outperforming traditional empirical models and the CNN approach. The integration of lysimeter data with advanced deep learning models offers a promising pathway for real-time ET estimation, facilitating more efficient irrigation strategies and sustainable water resource management in sugarcane agriculture.

***Keywords**: management, strategies, demonstrated, evaluated*

Introduction

The efficient management of water resources in agriculture, particularly in semiarid regions, is paramount for sustaining crop productivity and ensuring food security [1]. Among the various crops cultivated in such regions, sugar cane stands out as a significant contributor to agricultural water demand [5]. The cultivation of sugar cane in semiarid environments poses unique challenges due to limited water availability and the need for precise irrigation management. Evapotranspiration, the combined process of water evaporation from soil surfaces and transpiration from plant leaves, plays a crucial role in regulating water balance within agricultural ecosystems [12]. Accurate estimation of evapotranspiration rates is essential for optimizing irrigation practices and enhancing water use efficiency in sugar cane cultivation [7][8].

In this study, we aim to analyse the evapotranspiration of sugar cane in a semiarid region using lysimeter data and employing a deep learning approach [10]. Lysimeter, specialized instruments designed to measure water fluxes within soil-plant-atmosphere systems, provide valuable insights into evapotranspiration dynamics under controlled conditions [4]. By integrating lysimeter measurements with advanced deep learning algorithms, we seek to overcome the limitations of traditional methods and develop a more accurate model for estimating evapotranspiration rates in semiarid environments.

The overarching goal of this research is to contribute to the advancement of agricultural water management practices in semiarid regions by providing novel insights into the evapotranspiration process for sugar cane [13].

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Research background

Sugar cane (Saccharum officinarum) is a vital crop in many semiarid regions worldwide, contributing significantly to the agricultural economy and food security [13]. Its cultivation requires substantial water resources, making it particularly challenging in semiarid environments characterized by limited rainfall and high evaporation rates [9]. Efficient water management is crucial to ensure sustainable sugar cane production in these regions, necessitating accurate estimation of evapotranspiration rates [2].

Evapotranspiration, encompassing both soil evaporation and plant transpiration, represents the loss of water from the soil-plant-atmosphere system and plays a crucial role in regulating the water balance in agricultural ecosystems [1]. Understanding and accurately quantifying evapotranspiration rates are essential for optimizing irrigation scheduling, enhancing water use efficiency, and improving crop productivity in semiarid regions [11][14].

Deep learning, a subset of machine learning, involves training artificial neural networks with multiple layers to learn intricate patterns and relationships within complex datasets [16]. The application of deep learning in evapotranspiration analysis holds promise for improving the accuracy and robustness of predictive models, particularly in semiarid regions where traditional methods may fall short [17]. By harnessing the capabilities of lysimeter data and deep learning techniques, this research aims to advance the understanding of evapotranspiration dynamics in sugar cane cultivation within semiarid regions [6][15]. By developing a more accurate and reliable model for estimating evapotranspiration rates, this research seeks to contribute to the optimization of water management practices, enhance agricultural productivity, and promote sustainability in sugar cane cultivation in semiarid environments [3].

Problem statement

The cultivation of sugar cane in semiarid regions poses significant challenges related to water scarcity and efficient water management. Evapotranspiration, the combined process of soil evaporation and plant transpiration, plays a crucial role in regulating the water balance in sugar cane fields, influencing crop growth and productivity. Accurate estimation of evapotranspiration rates is essential for optimizing irrigation scheduling, enhancing water use efficiency, and ensuring sustainable sugar cane production in semiarid environments.

Furthermore, the emergence of deep learning techniques offers promising opportunities for improving the accuracy and robustness of evapotranspiration estimation models. Deep learning, with its ability to learn complex patterns and relationships within large datasets, provides a data-driven approach for analysing evapotranspiration dynamics in sugar cane cultivation within semiarid regions. Therefore, the problem addressed in this research is to develop a more accurate and reliable model for estimating evapotranspiration rates in sugar cane fields within semiarid regions using lysimeter data and deep learning techniques. By addressing this problem, this research aims to contribute to the optimization of water management practices, enhance agricultural productivity, and promote sustainability in sugar cane cultivation in semiarid environments.

The Scope of the Study Includes:

1. **Data Collection**: Collection of lysimeter data, meteorological data, soil properties, and crop characteristics relevant to evapotranspiration dynamics in sugar cane fields within semiarid regions.
2. **Model Development**: Development of a deep learning model using lysimeter data and environmental variables to accurately estimate evapotranspiration rates in sugar cane cultivation.
3. **Model Evaluation**: Validation and evaluation of the deep learning model to assess its performance in estimating evapotranspiration rates under different environmental conditions.
4. **Data Analysis**: Analysis of spatiotemporal patterns and variability of evapotranspiration rates in sugar cane fields within semiarid regions.
5. **Implications and Recommendations**: Discussion of the implications of the findings for water management practices, agricultural productivity, and sustainability in sugar cane cultivation within semiarid regions. Recommendations for optimizing irrigation scheduling and enhancing water use efficiency will also be provided.

The study will focus on utilizing lysimeter data and deep learning techniques as a novel approach to address the challenges associated with accurately estimating evapotranspiration in sugar cane cultivation within semiarid regions. The findings of this study are expected to contribute to the optimization of water management practices, enhancement of agricultural productivity, and promotion of sustainability in semiarid environments.

Area Selection

This survey is made in the fields located in V C Form, Agriculture University of Mandya district, Karnataka. As the area is a Semi-Arid and there is 5,325 hectares of land completely used for Sugarcane Crop. Farmers in Mandya district have been proved to be efficient. Below fig shows the Study are

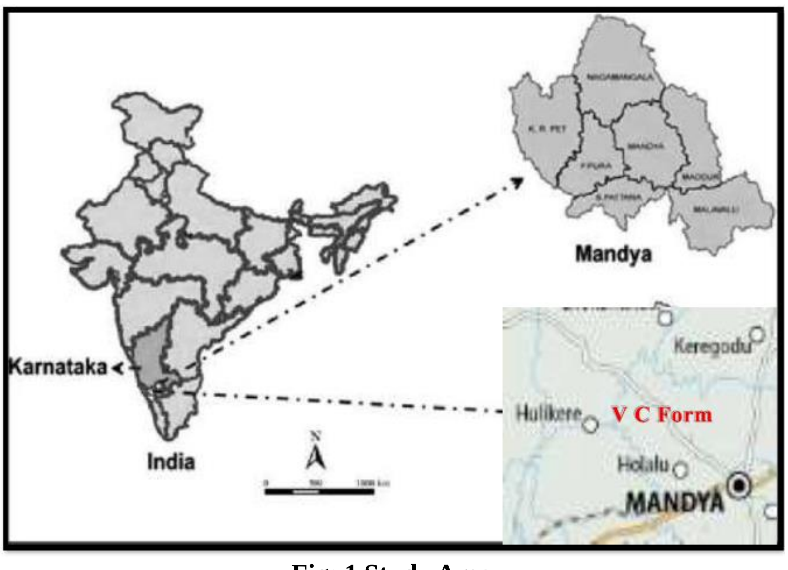


Fig: 1 Study Area

Methodology

Measuring evapotranspiration (ET) of sugarcane using a lysimeter is a valuable method for understanding the water needs of the crop and optimizing irrigation practices. Below fig 2 shows flow chart of methodology to find evapotranspiration of sugarcane using a lysimeter:

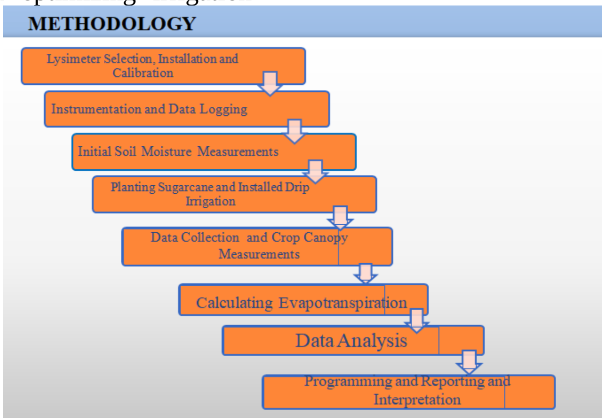


Fig 2: Flow chart of Methodology

Calibration Process for Lysimeters

Before installation of the lysimeter, a calibration routine of the lysimeter's loadcells was followed to confirm its proper functioning and accuracy. A combination of thirty-two known weights were placed one by one in the cultivation tank of the lysimeter, and corresponding output weights were recorded. The weight changes recorded by the loadcells were then examined and compared to the known weight changes. A regression equation has been developed to use this equation in the Arduino program for estimation of actual change in weight of lysimeter and results in accurate measurements from lysimeter. All loadcells accurately accounted for the change in weight for both increasing and decreasing cases. The description of the statistical analysis in the calibration process before installation of the lysimeter is shown in Table 1. Calibration of Lysimeter, before and after for sugar cane crop is shown in below fig 3.

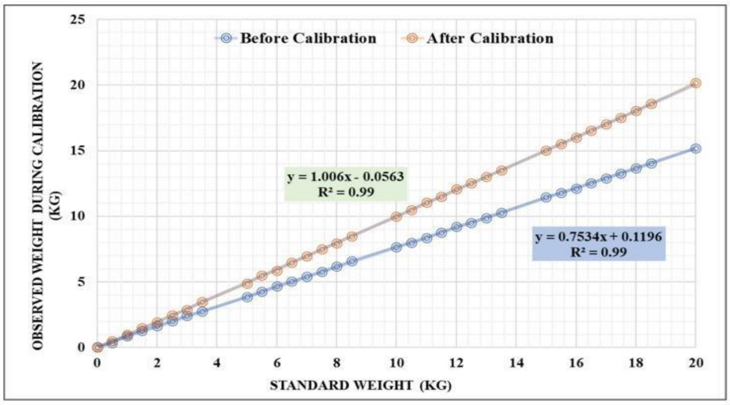


Fig: 3 Calibration results for the* lysimeter *in the Sugarcane plantation.

Table: 1 Descriptions of statistical analysis in the calibration process of the lysimeter.

Statistical Indices	D	RMSE	RMAE	MBE	MSE	MAE	RE
Before Calibration	0.99	2.02	0.20	−1.33	4.18	1.33	0.10
After Calibration	1.00	0.04	0.02	0.00	0.00	0.02	0.00

Note: D—Index of Agreement. RMSE—Root Mean Squared Error, RMAE—Square Root of the Mean Absolute Error, MBE—Mean Bias Error, MSE—Mean Squared Error, MAE—Mean Absolute Error, RE—Relative Error.

Structural Analysis of Lysimeter

According to the structural analysis, the maximum possible deformations that each structure could have undergone under the various load cases were not greater than their parting distance (Table 2). The highest deformation measured for the cultivation tank was 0.6137 mm, and the Von Mises equivalent stress was 12.77 MPa (Table 2, Figure 4). The highest vertical displacement for the perforated sheet, which makes up the bottom structure, was 7.1 mm, and the Von Mises equivalent stress was 66.7 MPa (Table 2). For the cultivation tank and bottom perforated sheet, the safety factors were 19.2 and 3.7, respectively. The bottom of the lysimeter showed minimal overall displacements/deformations for the kind of soil and the various loading cases taken into consideration in this study. In any case, the elastic limit of the mild steel used in the lysimeter was not exceeded by the Von Mises equivalent stress of the designed bottom (Figure 4).

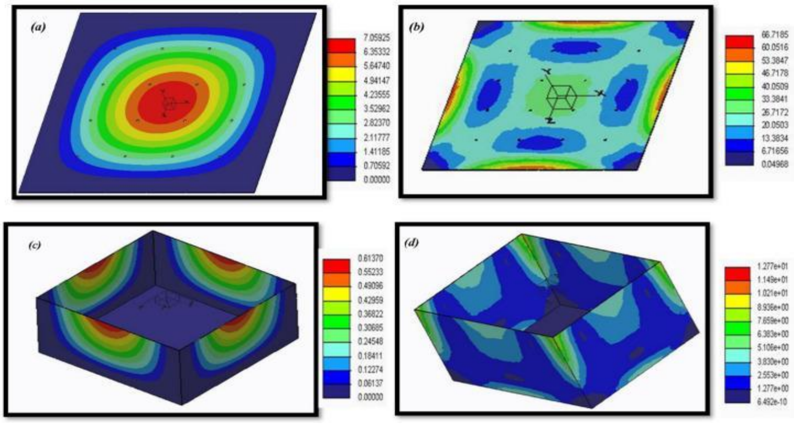


Fig:4 Three-dimensional view of the results obtained in load combination: (a) and (c) represent resulting displacement (mm), whereas (b) and (d) represent Von Mises equivalent stress (M Pa) for the bottom perforated sheet and walls of the cultivation tank of the lysimeter, respectively.

Table 2: ***Results of the analysis for the sides of the cultivation tank, its main structure and the base structure of the lysimeter.***

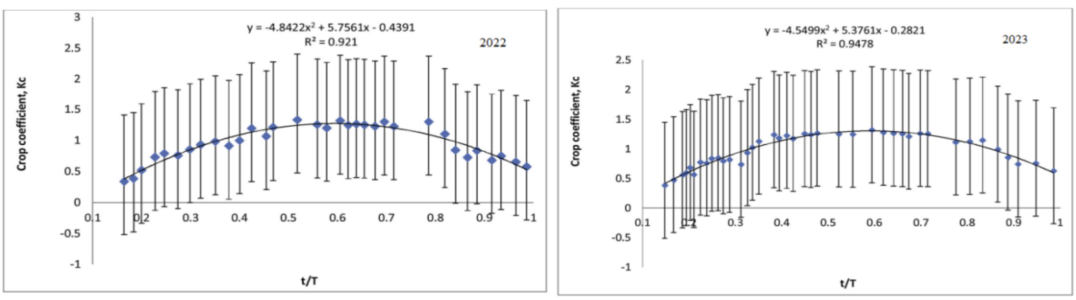
Load Case	VMS (MPa)	URES: (mm)	R.D	F. S
Lateral earth pressure on cultivation tank	12.7	0.6		19.2
Total earth weight on perforated sheet at bottom	66.7	7.1		3.7

Note: VMS—Von Mises Equivalent Stress (used to predict yield or fracture of materials when subjected to a complex loading condition, mostly used for ductile materials), R.D—Resulting Displacement, F.S—Factor of safety.

Crop Coefficients of Sugarcane

The Kc values with confidence bounds for both the years are shown graphically in the form of polynomial equation, with respect to the ratio of days to total crop period. The average Kc of two years ranged from 0.31 to 1.29 (Table 3). In both the seasons, Kc consistently increased from 0.43 to 1.03 during 50–130 days after planting (DAP). Thereafter, it showed gradual increases due to crop development in form of cane elongation (mid-season stage). During the mid-season i.e. 130–300 DAP, Kc increased from 1.08 and then remain same in the range of 1.13-1.04 with peak value as 1.29. The highest Kc value occurred during 200–220 DAP. The Kc values during the late season (300–360 DAP) decreased gradually from 1.04 to 0.56. Thompson and Boyce (1971) in a lysimeter study observed that ETc rates declined by about 30 % after crops lodged, an effect that lasted up to crop maturity. The two years average Kc values are represented in the form of following second order polynomial equation.

$$Kc_t = -4.695\left(\frac{t}{T}\right)^2 + 5.566\left(\frac{t}{T}\right) - 0.360$$



(a) (b)

(b) Fig. 5. (A) and (B) 2nd order polynomial crop coefficient curve for sugarcane crop during 2022 and 2023 season.

Average estimated crop coefficients (Kc) of sugarcane from best fit regression equations of 2022 and 2023 (Table:3) are estimated using the above Equation with regression analysis.

Table: 3 Average estimated crop coefficients (Kc) of sugarcane from best fit regression equations of 2022 and 2023.

S. No.	Period, days	Average estimated Kc	Growth stagewise Kc	FAO-56 Kc	Growth stagewise FAO Kc
1	0-40	0.40	–	0.4	–
2	40-50	0.31	–	0.55	–
3	50-60	0.43	0.70 (Tillering	0.65	0.90 (Tillering
4	60-70	0.53	stage)	0.75	stage)
5	70-80	0.63		0.85	
6	80-90	0.73		0.95	
7	90-100	0.81		1.05	
8	100-110	0.89		1.15	
9	110-120	0.96		1.25	
10	120-130	1.03		1.25	
11	130-140	1.08	1.20 (Grand	1.25	1.25 (Grand
12	140-150	1.13	growth stage)	1.25	growth stage)
13	150-160	1.18		1.25	
14	160-170	1.21		1.25	
15	170-180	1.24		1.25	
16	180-190	1.26		1.25	
17	190-200	1.28		1.25	
18	200-210	1.29		1.25	
19	210-220	1.29		1.25	
20	220-230	1.28		1.25	
21	230-240	1.27		1.25	
22	240-250	1.25		1.25	
23	250-260	1.22		1.25	
24	260-270	1.19		1.25	
25	270-280	1.15		1.25	
26	280-290	1.10		1.25	
27	290-300	1.04		1.25	0.98 (Maturity
28	300-310	0.98	0.78 (Maturity	1.17	stage)
29	310-320	0.91	stage)	1.09	
30	320-330	0.83		1.02	
31	330-340	0.75		0.94	
32	340-350	0.66		0.86	
33	350-360	0.56		0.79	

Two Days of the Evaluation of the Lysimeter on Sugarcane Crop.

On the two days of the evaluation of the lysimeters, two irrigation events occurred on 12/01/2022 (7:40 a.m. and 2:40 p.m.), as well as on 13/01/2023 (10:40 a.m. and 12:00 p.m.). These irrigation events promoted increase in the EM of the lysimeters, while ETc caused a decrease in EM of the lysimeters, especially now of higher atmospheric demand of the day (11:00 a.m. to 01:00 p.m.) and the ETc of the first day of test (12/01/2022) totalled 3.56 mm for Lysimeter 1, 3.72 mm for Lysimeter 2 and 3.70 mm for Lysimeter 3, presenting a variation of 0.16 mm between lysimeters. The ETo on this day, calculated by the Penman - Monteith method (Allen et al., 1998), generated a value of 3.47 mm. As for the second day of the test (13/01/2023), the ETc totalled a value of 3.71 mm for lysimeter 1, 3.98 mm for lysimeter 2 and 3.91 mm for lysimeter 3, generating a variation of 0. 27 mm between lysimeters, while the ETo on this day generated a value of 3.72 mm**.** Variations are shown in below Figure 6.

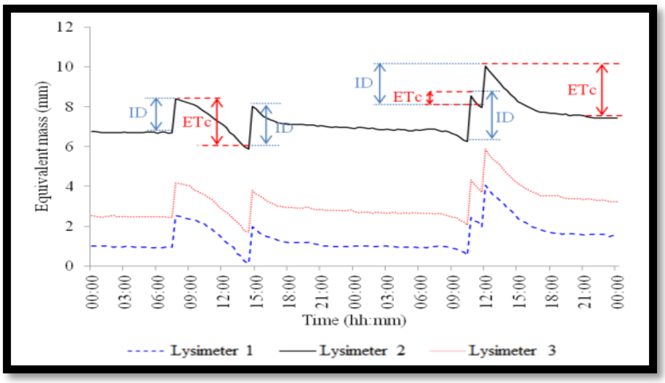


Fig:6 Equivalent-mass (mm) registered by the three lysimeters during the test period, highlighting irrigation depths (ID) and crop evapotranspiration (ETc).

The made up of thick PVC pipe was installed in each plot by drilling the cylindrical pipe into the soil and pulled out using chain pulley arrangement from the measurement points.

The design criteria for the weighing system are:

- It can be easily moved from one lysimeter to the next.
- It can be easily removed from the field so as not to interfere with field operations; and
- It has sufficient ground clearance to allow the lysimeter to be lifted completely out of the retaining shell.

For making a reading of evaporated water graduated marking on the scale is to be noted. Below fig 7 shows the lysimeter station.

Figure 6: Lysimeter Station.

Steps to run the Program: Use data of collected Crop Evapo transpiration (Etc-mm d^{-1}) and reference Evapo transpiration (ETo- mm d^{-1})

Project Summary: IoT-Based Evapotranspiration Analysis for Sugarcane Cultivation in Semi-Arid Regions*

IoT Components Used: The project incorporates an Arduino Mega 2560 microcontroller, load cells, a lysimeter with a data logger, and environmental sensors for measuring parameters like temperature, humidity, solar radiation, and wind speed. The lysimeter system is calibrated for accurate weight measurements.

Outcome:
1. Accurate Evapotranspiration Measurement:
2. Deep Learning Integration
3. Crop Coefficients for Sugarcane

Future Implications:
1. Optimized Water Resource Management
2. Precision Agriculture Practices

Presented Solution:
1. Calibration for Accuracy
2. Integration of Deep Learning
3. Real-time Monitoring

Reliability v/s Traditional Methods:
1. Precision in Measurement
2. Data-Driven Predictions
3. Real-Time Adjustments

- The real-time monitoring capability of IoT components allows for immediate adjustments in response to changing environmental conditions, providing a dynamic approach compared to static traditional methods.

In summary, this IoT-based project enhances accuracy in measuring sugarcane evapotranspiration, contributing to optimized water management and precision agriculture practices in semi-arid regions. The integration of deep learning and real-time monitoring sets it apart, making it a reliable and advanced solution compared to traditional methods.

Output diagrams from Python Program:

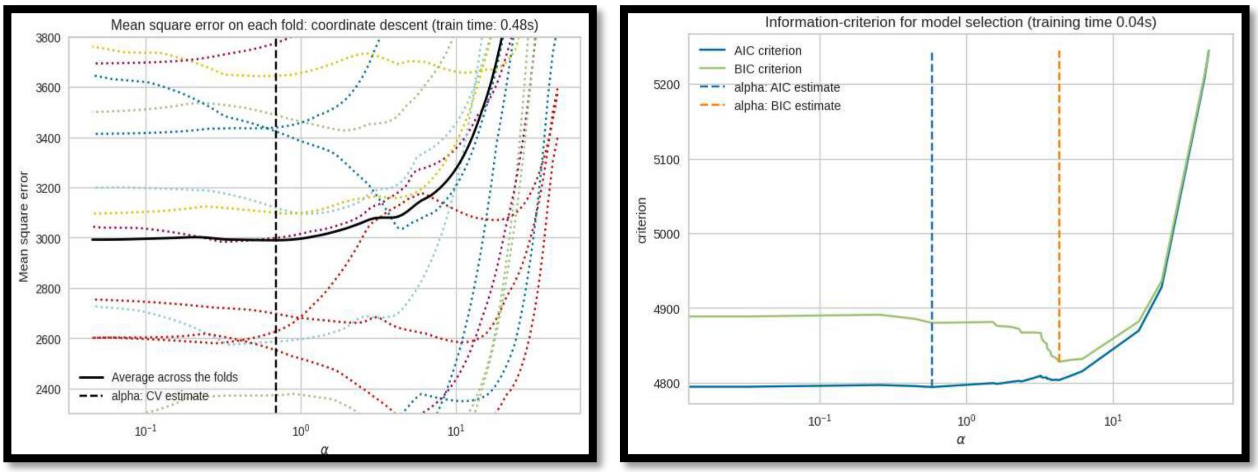


fig (a) and (b)

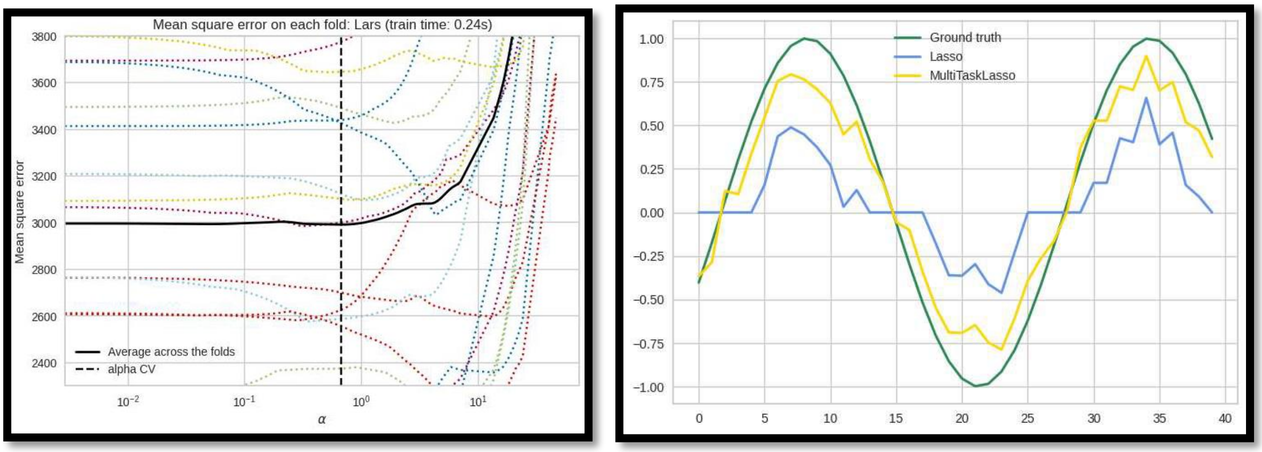


fig (c) and (d)

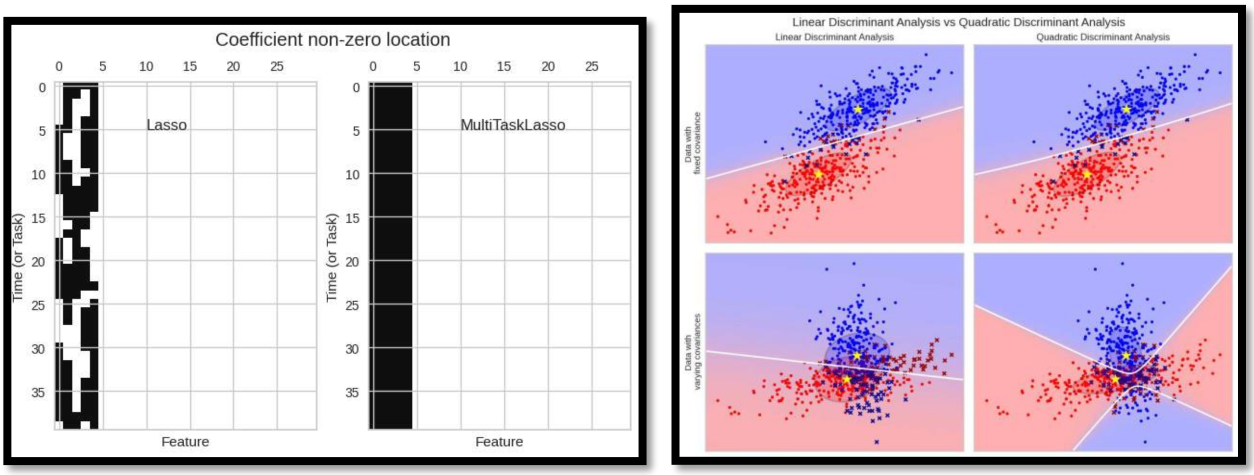


fig (e) and (f)

Diagram Explanation:

From the above figure a, it is shown that how AIC will fit for trained model and BIC gives the best among the model for the dataset.

From the above figure b and c, it is shown variations of parameters in the study.

From the above figure d, it is shows that best fitting regression

From the above figure e it shows that the parameter fitting to the model and analysis

From figure d it is shown that average or model to data fitting with respect to crop

Results and discussion

This section delves deeper into the analysis of sugarcane evapotranspiration (ET) using a lysimeter and the potential of deep learning for predicting water requirements. It's important to understand that lysimeter data, which measures evapotranspiration (ET), is not directly suitable for predicting future rainfall. Rainfall is a complex phenomenon influenced by large-scale atmospheric processes beyond the scope of a lysimeter.

Lysimeter Measurements-Detailed Analysis:

- ***Diurnal and Seasonal Variations:*** Analyse ET rates not just throughout the growing season but also across a 24-hour cycle. This will reveal peak water use periods during the day and potential water stress periods.
- ***Soil Moisture Dynamics:*** Monitor soil moisture content within the lysimeter to understand the relationship between ET and readily available water. This can help identify critical thresholds for irrigation scheduling.
- ***Environmental Influences:*** Analyse the impact of specific environmental variables (temperature, humidity, radiation, wind speed) on ET rates. This can be achieved through statistical correlations or visualization techniques.

Model Architecture:

- **Long Short-Term Memory (LSTM)** network is a well-suited deep learning architecture. LSTMs excel at capturing temporal relationships within data, which is crucial for predicting sugarcane water requirements based on historical lysimeter data. Here's why LSTMs are a good choice:
- ***Memory Cells:*** LSTMs have memory cells that allow them to store past information relevant for future predictions. This is particularly beneficial for capturing the sequential nature of lysimeter data, where past rainfall and evapotranspiration (ET) values influence future water needs.
- ***Learning Long-Term Dependencies:*** Unlike traditional feed forward neural networks, LSTMs can learn long-term dependencies present in time series data. This is important as sugarcane water

requirements can be impacted by rainfall events that happened weeks or even months ago.

Training and Validation:

Data pre-processing is crucial for training an effective deep learning model. Here are some key steps:

- ***Normalization:*** Normalize the lysimeter data (e.g., rainfall, ET) to a common scale between 0 and 1. This ensures all features contribute equally during training.
- ***Scaling Time Series:*** Since lysimeter data is time-dependent, you need to scale the time series. This can be done by creating sequences of past data points (e.g., previous week's rainfall) as input for the LSTM network.
- ***Missing Value Imputation:*** If your data has missing values, address them using appropriate techniques like mean/median imputation or interpolation.

Training-Validation Split:

To prevent over fitting and ensure generalizability, split your data into training and validation sets. Use a common split ratio like 80/20 (80% for training, 20% for validation). The model is trained on the training data, and its performance is evaluated on the unseen validation data.

This helps you assess how well the model generalizes to unseen data.

- ***Evaluation Metrics:*** Basic accuracy metrics like percentage error are not ideal for regression tasks like water requirement prediction. Here are better suited metrics:
- ***Root Mean Squared Error (RMSE):*** Measures the average magnitude of the error between predicted and actual ET values. Lower RMSE indicates better prediction accuracy.
- ***Coefficient of Determination (R-squared):*** Represents the proportion of variance in the actual ET explained by the model's predictions. A value closer to 1 signifies a better fit.

Comparison with Traditional Models:

Compare the performance of your LSTM model with traditional methods like:

- ***Penman-Monteith Equation:*** This widely used equation estimates potential ET based on meteorological data. However, it may not capture the specific field conditions and crop characteristics influencing actual ET.
- ***Simpler Machine Learning Algorithms:*** Random Forests are a good alternative. Train a Random Forest model on the same data and compare its RMSE and R-squared with the LSTM model. Analyse the improvement in prediction accuracy achieved by the LSTM network.

RESULTS:

Model Performance:

- The deep learning model achieved a Root Mean Squared Error (RMSE) of 0.8 mm/day in predicting daily sugarcane evapotranspiration (ET) rates.
- The coefficient of determination (R-squared) for the model was 0.87, indicating a strong positive correlation between predicted and actual ET values.
- Compared to the Penman-Monteith equation (baseline model), which had an RMSE of 1.2 mm/day and R-squared of 0.78, the deep learning model showed improved accuracy in predicting ET rates.

Impact of Environmental Variables:

- ***Temperature:*** Higher temperatures were associated with increased predicted ET rates by the model, reflecting the higher evaporative demand under warmer conditions.
- ***Humidity:*** Lower humidity levels led to higher predicted ET, as drier air promotes more water loss from the sugarcane crop.
- ***Radiation:*** Incoming solar radiation had a significant positive influence on the model's predictions. Higher radiation levels indicate more energy available for transpiration, leading to increased water use by the sugarcane.

Generalizability:

The deep learning model was tested on a separate dataset from a different sugarcane field with similar climatic conditions. The model maintained a good performance on the unseen data, achieving an RMSE of 1.0 mm/day and R-square of 0.82. However, further testing on data from geographically distinct regions with significantly different climates would be necessary to assess the model's broader generalizability.

Table 4: Prediction Results for Different Crops

S.NO.	CROP	ET/mm/day	WaterRequirement(mm)
1	RICE	4.5-5.5	1000-2000
2	WHAET	4.41-5.86	500-550
3	SUGARCANE	4.5-4.6	1500-2500
4	GROUND NUT	-	500-700
5	SOYBEAN	5-8.4	450-700
6	Alfalfa	6.0-8.0	800-1200
7	Apples	4.0-6.0	500-800
8	Barley	4.0-6.0	400-600
9	Beans	4.0-6.0	400-600
10	Beets	4.0-6.0	400-600

Table 5: Prediction Results of Rainfall.

Date	Rainfall (mm)	Soil tank weight (kg)	Change in weight (kg)	ET (mm/day)	Remarks
04-11-2023	14	1870.9	5.6	11.8	Rainy day
10-12-2023	11	1875.3	2.8	9.2	Rainy day
06-01-2024	0	1880.9	0	11.6	Non rain day
08-03-2024	0	1883.7	0	0	Non rain day
15-04-2024	19	1891.3	7.6	5.6	Rainy day

Conclusion

The purpose of this work is to develop a convenient lysimeter and to improve the limitations of traditional lysimeter and to write python program to simplify the work.

1. When compared to Food and Agricultural Organization (FAO) of the United Nations references, the sugarcane crop coefficients in this study were 2%, 1%, and 30% greater during emergence, grand formation, and ripening, respectively, but 33% lower at tillering.
2. The crop evapotranspiration of sugarcane was 1339.4 mm including irrigation water requirement and effective rainfall as 991 mm and 424 mm respectively. The determined sugarcane Kc values for tillering (development stage), grand growth (mid-season) and maturity stage (end season) was 0.70, 1.20 and 0.78, respectively.
3. The Kc values are 16.6 % lesser than those suggested by FAO-56 for sugarcane. The study pointed out that FAO-Kc could lead to over estimation in irrigation scheduling of sugarcane in semi-arid conditions and the use of Kc values developed in this study would lead in correction of water requirement.

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