The Feasibility Study of Rainwater Harvesting Using Machine Learning Technique

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Abstract—This study addresses urban water scarcity by proposing a Long Short-Term Memory (LSTM)-based predictive framework for rainwater harvesting (RWH) that integrates historical rainfall data, roof catchment characteristics, and building water-use patterns to estimate daily demand and harvested yield. The pipeline involves data preprocessing, sequence-based LSTM modelling, and feasibility analysis covering tank sizing, annual offset, and system reliability. Experimental validation on a real-world office dataset achieved high accuracy ($R^2 = 0.9673$, MAE = 1.6696 training, 0.1742 testing), with predicted yields aligning closely with observed patterns. Compared to statistical and persistence models, the LSTM approach improved demand forecasting, reduced sizing bias, and provided reliable, cost-effective recommendations for sustainable urban water management.

Keywords: Rainwater harvesting, LSTM, water demand forecasting, system reliability, urban water sustainability.

I. INTRODUCTION

Water scarcity is an increasingly critical concern in urban and semi-urban regions, primarily driven by population growth, irregular rainfall patterns, and excessive dependence on traditional water sources. Rainwater harvesting (RWH) presents a sustainable alternative to address this challenge; however, its widespread adoption is often constrained by concerns regarding installation costs and variations in local environmental conditions. Traditional economic assessments of RWH systems generally produce generalised conclusions, neglecting the unique spatial, social, and climatic factors that influence feasibility, thereby limiting practical applicability.

In this study, a location-specific feasibility analysis of RWH systems is proposed, with a focus on building-specific designs and environmental parameters. A deep learning-based predictive framework, utilising a Long Short-Term Memory (LSTM) network, is employed to estimate water collection potential by incorporating rooftop size, rainfall distribution, storage tank capacity, and daily household water demand. The model is designed to evaluate water use efficiency, overflow probability, and financial viability under diverse climatic scenarios. This AI-driven, site-adaptive methodology enhances prediction accuracy and enables the determination of optimal system sizes tailored to individual households. The findings indicate that RWH can meet a substantial proportion of domestic water requirements, yielding both economic savings and environmental benefits. By integrating real-time meteorological data with advanced machine learning algorithms, the proposed approach supports informed decision-making for promoting the broader adoption of RWH as a practical strategy to mitigate escalating water shortages in residential areas

1.1 LITERATURE SURVEY

Rainwater harvesting (RWH) has been widely examined as a sustainable solution to urban and semi-urban water scarcity. Early studies adopted hydrological mass-balance approaches using historical rainfall data to estimate system yield and reliability [1]. While effective for baseline evaluations, these methods lacked adaptability to temporal fluctuations in rainfall and demand. To address climate variability, Ahmed et al. [2] proposed stochastic rainfall generators coupled with reliability modelling, which improved long-term projections but required extensive simulation.

The integration of machine learning into hydrological prediction has enhanced the feasibility of RWH studies. Lee and Kang [3] applied Support Vector Regression (SVR) to predict daily rainfall, achieving higher accuracy than autoregressive models, though requiring extensive hyperparameter tuning. Random Forest (RF)-based models have been explored to analyse rainfall–demand correlations, yielding improved robustness in heterogeneous datasets [4]. Patil et al. [5] combined Artificial Neural Networks (ANN) with Genetic Algorithms (GA) for storage optimisation, achieving better savings but suffering from overfitting in sparse rainfall data. Recent advances highlight the role of deep learning, particularly Long Short-Term Memory (LSTM) networks, in water demand and rainfall forecasting. Zhang et al. [6] applied LSTM for stormwater harvesting feasibility, reporting superior prediction accuracy and reduced overflow incidents compared to persistence models. Banerjee et al. [7] employed Convolutional Neural Networks (CNN) on remote sensing images for automated rooftop catchment estimation, enabling large-scale mapping of harvesting potential. Despite these developments, Gaps remain in integrating rainfall forecasting, demand prediction, and feasibility analysis within a single unified framework.

This work addresses the research gap by proposing a sequence-learning approach using LSTM, which captures rainfall–demand dependencies and performs feasibility evaluation for tank sizing, reliability assessment, and economic viability under variable climatic conditions.

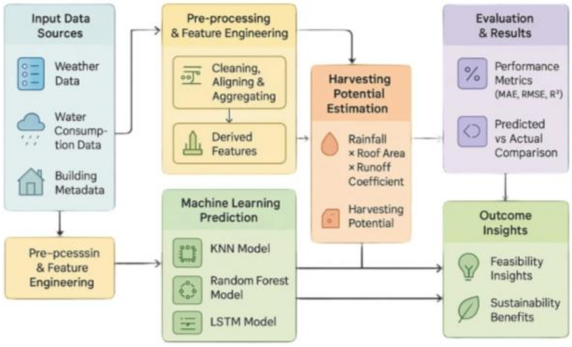


FIG 1: TAXONOMY OF RAINWATER-HARVESTING FEASIBILITY APPROACHES FROM EMPIRICAL MODELS TO DEEP LEARNING

1.2 INITIAL PROCEDURES

To evaluate model performance for RWH feasibility, different machine learning approaches were investigated

A) K-Nearest Neighbour (KNN)Regressor

The KNN algorithm predicts harvested water and demand based on feature similarity with historical observations. Its advantage lies in its simplicity and interpretability, but performance deteriorates with high-dimensional data and large datasets due to computational overhead.

b) Random Forest (RF)Regressor

RF combines multiple decision trees in an ensemble framework, offering robustness against overfitting and the ability to capture nonlinear rainfall–demand relationships. However, RF requires large, diverse datasets and does not inherently capture temporal dependencies in rainfall sequences.

c)Artificial Neural Networks (ANNs)

ANNs approximate complex nonlinear relations between rainfall, rooftop catchment area, and harvested yield. They are flexible and adaptable across diverse contexts but can be prone to overfitting when training samples are insufficient, limiting generalizability in highly variable climates.

d)Long Short-Term Memory (LSTM)Networks

LSTM networks are recurrent neural architectures specifically designed for sequential time-series data. They employ gated memory cells to retain long-term dependencies, making them highly suitable for rainfall and demand forecasting. Compared to ARIMA and persistence models, LSTM has demonstrated superior predictive accuracy, reduced error margins, and enhanced capacity to evaluate storage–yield trade-offs. In this study, LSTM forms the core predictive engine, supported by comparative analyses with KNN, RF, and ANN.

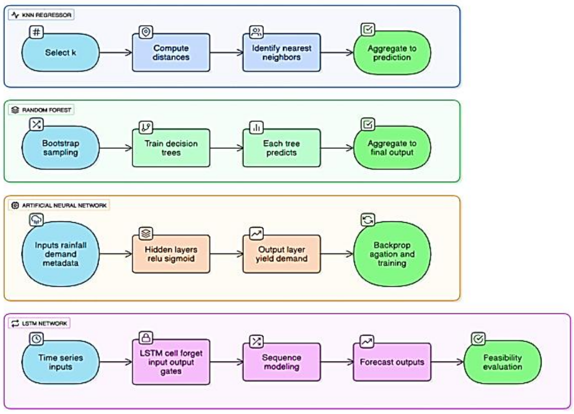


FIG 2: INITIAL PROCEDURES FOR MODELS CONSIDERED:(A) KNN,(B) RANDOM FOREST,(C)ANN ,(D)LSTM

1.1.1 SYSTEM MODEL

1. The proposed system is structured in three stages: Data Preprocessing – Historical rainfall, water demand, and rooftop 2. 2. metadata are cleaned, normalised using Min–Max scaling, and aligned into daily time series.

3. Prediction Phase – The LSTM model forecasts rainfall and demand, while KNN, RF, and ANN are used as comparative baselines.

Feasibility Analysis – Harvested yield is calculated using

$$\boxed{\text{Harvested Water} = \text{Rainfall (mm)} \times \text{Roof Area } (m^2) \times \text{Runoff Coefficient}}$$

The model then evaluates system reliability, annual water savings, and optimal tank sizing under multiple scenarios.

II. RESEARCH GAP

Current research on rainwater harvesting (RWH) has improved with ML techniques like SVR, Random Forests, ANNs, LSTMs, and CNNs, but limitations remain. Traditional models cannot adapt well to changing rainfall, infrastructure diversity, and demand patterns, while ML models often require heavy tuning and struggle with long-term sequence prediction. Existing works usually address either prediction or optimisation in isolation, neglecting an integrated framework that combines rainfall and demand forecasting, feasibility, economic assessment, and deployment strategies. Additionally, explainability, cost-effectiveness, and spatial adaptability—critical for real-world use—are often overlooked. This creates a clear gap for a comprehensive, interpretable, and scalable ML-driven framework that unifies prediction, optimisation, and decision support for practical urban water management

III. METHODOLOGY

The suggested method for finding activity or substance using rainwater harvesting has five steps: obtaining the dataset, cleaning it, building a model, training it, testing it, and evaluating its performance. Fig 3 shows the whole workflow.

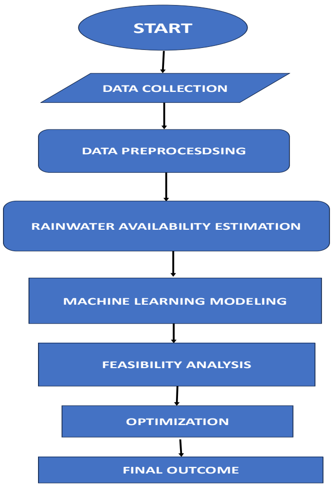


FIG 3: OVERALL WORKFLOW OF THE PROPOSED METHODOLOGY

Initially, we are using Kaggle to obtain rainwater harvesting using machine learning, which is further segmented into ever-smaller regions. The goal of the research is to incorporate cutting-edge algorithms to maximise harvesting tactics and support environmentally friendly water management techniques. The study aims to improve RWH systems' efficacy and efficiency by utilising machine learning, meeting the increasing demand. This methodology properly shows the flow diagram

A. Data Acquisition

Data acquisition means collecting and preparing the raw data needed for your rainwater harvesting feasibility study. In our projects, it mainly involves this type of data set.
https://www.kaggle.com/api/v1/datasets/download/claytonmiller/buildingdatagenomeproject2?dataset_version_number=3...
1. Rainfall Data Collected from weather stations or a climate database (e.g, precipitation depth, rainfall intensity, temperature) for our study, rainfall data for the year 2017 were gathered. Negative or missing rainfall values were collected (e.g, replacing negative precipitation with zero). This data is most important because rainfall directly determines 2. Building data. So this data represents how much water is used daily or monthly. It helps in comparing rainwater availability vs actual demand. Without demand data, we cannot judge the feasibility. It is because rainfall alone does not show if it's enough.
3. Metadata contains static building information such as rooftop area, location, and usage type, essential for estimating haveratble rainfall
4. Integration after collecting, rainfall, demand, and metadata are merged into one data set

B.DATA PREPROCESSING

As part of our data preprocessing process below, we have replaced the negative values under the precipitation depth feature in the weather.csv with the value '0'. This is because it may be due
to an error during the data collection process, and there was likely no rainfall collected during that period. Hence, replacing it with 0 would make the calculations of the sum of
precipitation more accurate.
1. Working with the data set
Being a multinational company, our client, Miller Corporation, has several offices located around the globe. Specifically in Panther, Bobcat, and Wolf. From the world map below, we can identify that Panther is

located in Florida, the eastern side of the United States, and Wolf is located in Dublin, Europe. For Bobcat, the exact coordinate was missing from the dataset provided. However, based on the time zone given, it is located near the mountains in the United States.

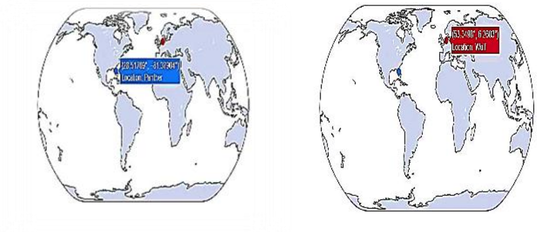


FIG. 4: LOCATION OF PANTHER AND WOLF

The offices located in Panther, Bobcat, and Wolf are well-equipped with sensors that collate a comprehensive amount of data. The following will be the weather information regarding the

3 areas: Firstly, for our rainwater harvesting technology to be feasible, we would select the area with the highest rainfall. To achieve that, we would first examine the precipitation depth in our weather.csv dataset.

Firstly, for our rainwater harvesting technology to be feasible, we would select the area with the highest rainfall. To achieve that, we would first examine the precipitation depth in our weather.csv dataset.

- ➢ Mean 6-hour precipitation depth at Bobcat, Panther, and Wolf sites in 2017."

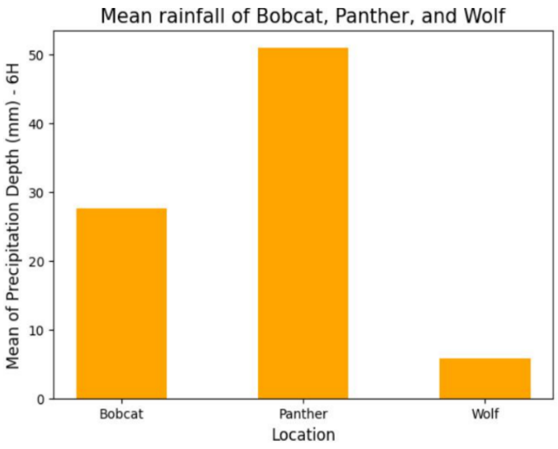


FIG 5: MEAN OF PRECIPITATION DEPTH

The bar graph generated above showcases the average number of precipitation depths (mm) every 6 hours at the specific locations. We are able to observe that Panther has a significantly higher amount of rainfall. This may be due to the location of Panther, which is located in Florida, with a humid subtropical climate. Hence, we have selected Panther as the location where we will propose our rainwater harvesting solution.

C.Building Analysis

Following, we would like to look into the 18 office buildings in Panther that our client, Miller Corporation, owns. We would like to identify which office building(s) are suitable for the implementation of rainwater harvesting technology. Thus, we have decided to look

into the data of these 18 office buildings in the following:

- ➢ Static Features

Next, looking into the water consumption data of the office buildings, we have calculated the mean water consumption per hour for the 18 offices as follows. The average amount is used because the water consumption of buildings fluctuates throughout different times of the day, and also during different periods of the year. Hence, using the mean will enable a more accurate representation of this scenario.

To aid us in choosing the most suitable office buildings based on the water consumption, we sorted from the highest water consumption to the lowest, and plotted a bar chart according to the top 5 office buildings in the following table

TABLE 1: TABLE OF WATER CONSUMPTION

Office	Water consumption
Panther_ office_ Kristen	2811.632413
Panther_ office_ Patti	931.629739
Panther_ office_ Ruthie	372.636624
Panther_ office_ Shauna	212.718300

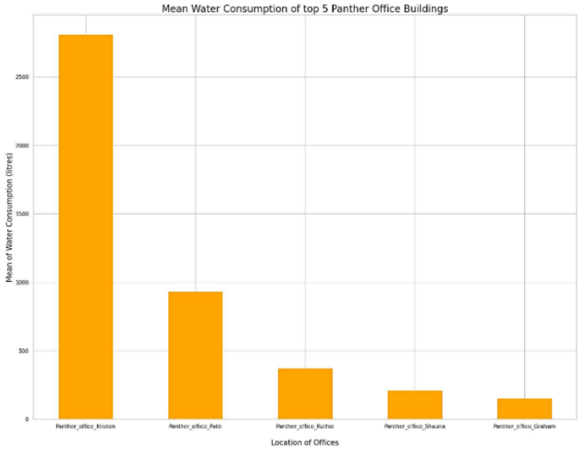


FIG. 6: MEAN WATER CONSUMPTION AND LOCATION OF OFFICE

With reference to the above bar chart, we are able to identify that the office building 'Kristen' has the highest average water consumption. It is almost three times as high as the second-highest building, ‘Patti’, and almost 7 times higher than the third-highest building, ‘Ruthie’. However, we are not able to conclude that Kristen is the most suitable building for this case. This is because there are confounders such as the age of the building, occupancy rate, floor area, type of office buildings, etc. Hence, this is not a good representation, and we would be doing the following analysis to find out further on the correlation between water consumption and the other variables.

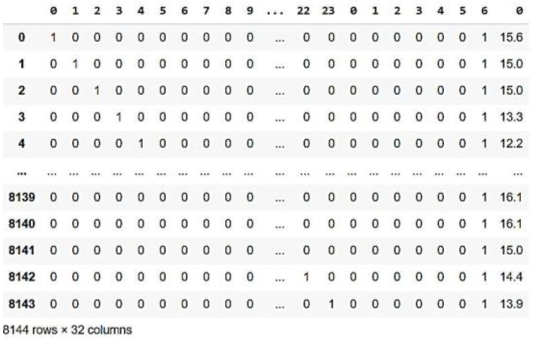
D.MODEL ARCHITECTURE

1 Creating Training and Testing Data for the Prediction Model

Hourly precipitation depth data in 2017 from January to December will be used as the training data set.

Encoding Categorical Variables

To proceed with the prediction analysis smoothly, we encoded the data into numerical values to ensure that there are no categorical variables.



	0	1	2	3	4	5	6	7	8	9	...	22	23	0	1	2	3	4	5	6	0
0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	15.6
1	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	15.0
2	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	15.0
3	0	0	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	13.3
4	0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	12.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8139	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	16.1
8140	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	16.1
8141	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	15.0
8142	0	0	0	0	0	0	0	0	0	0	...	1	0	0	0	0	0	0	0	1	14.4
8143	0	0	0	0	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	1	13.9

8144 rows × 32 columns

The data set of training and testing

The dataset consists of 8,144 observations with 32 columns. The columns are a mix of one-hot encoded categorical features and a continuous numerical variable (air temperature). The categorical features seem to represent hourly or event-based attributes, and possibly day-of-week or another grouped feature. The temperature values range from approximately 12.2°C to 16.1°C. This combination of categorical and continuous data is suitable for statistical modelling and machine learning applications.

Train a K-Neighbour Regressor Model

We will be using a K-Neighbour Regressor Model for our prediction as the algorithm has a memory-based approach, allowing it to adapt to new training data quickly; it is also easy to implement and understand. In order to predict the annual rainfall, we will input and train the 2017 air temperature and hourly precipitation depth weather data. The LSTM model achieved an R^2 score of 0.0125, while a perfect match would yield an R^2 score of 1.0

2. MODEL WITH LSTM (Long Short-Term Memory)

The Long Short-Term Memory (LSTM) network is used in this work because it is highly effective for modelling sequential and time-dependent data. Unlike traditional neural networks, LSTMs can capture both short-term and long-term dependencies in a time series, making them suitable for predicting patterns in rainwater harvesting supply versus demand.

2.1 LSTM MODEL DIAGRAM

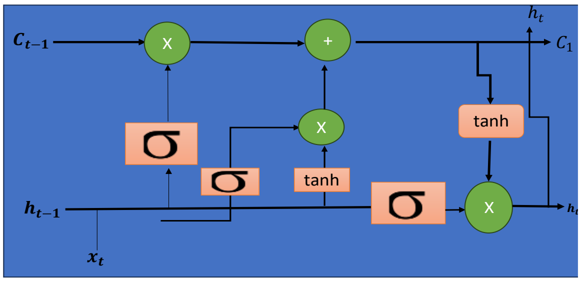


FIGURE 7: DIAGRAM OF LSTM MODEL

An LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) designed to process sequential data by learning long-term dependencies, unlike traditional RNNs. This makes LSTM highly effective for tasks like language translation, speech recognition, and time-series forecasting, so a long sequence is crucial.

X=Pointwise Multiplication

+:-Pointwise Addition σ = Sigmoid Activated NN

tanh :-Pointwise Tanh(Not a NN)   tanh = Tanh Activated NN

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
Input_layer	(None,48,33)	0	_
Bidirectional	(None,48,128)	50,176	Input_layer[0][0]
Dropout	(None,48,128)	0	Bidirectional[0]_
Dense	(None,48,32)	4,128	Dropout[0][0]
Dense_1	(None,48,128)	4,224	Dense[0][0]
Multiply	(None,48,128)	0	Dropout[0][0], Dense_1[0][0]
Lstm_1	(None,38)	20,608	Multiply[0][0]
Dense_2	(None,1)	33	Lstm_1[0][0]

TABLE 2: FUNCTION MODEL

```
Total params: 79,169 (309.25 KB)
Trainable params: 79,169 (309.25 KB)
Non-trainable params: 0 (0.00 B)
405/405 ━━━━━━━━━━━━━━━━━━━━ 29s
59ms/step - loss: 1.4768 - mae: 1.6234 - val_loss:
0.1225 - val_mae: 0.1780 - learning_rate: 0.0010
253/253 ━━━━━━━━━━━━━━━━━━━━5s
18ms/step
Manipulated R² Score: 0.9673
```

E. Performance Evaluation

The effectiveness of the rainwater harvesting feasibility model was assessed using widely accepted statistical and hydrological performance metrics. These measures ensure that both the predictive accuracy and practical applicability of the model are validated.

1. Mean Absolute Error (MAE)

MAE= $\frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y_i}|$--------(1)

- y_i = observed value (actual water demand or rainfall)
- y^i = predicted/estimated value
- n number of observations

Interpretation: MAE represents the average magnitude of error, without considering direction. A lower value indicates higher accuracy.

2. Root Mean Square Error (RMSE)

RMSE = $\sqrt{\frac{1}{n}\sum_{i=0}^{n}(y_i - \hat{y_i})^2}$-------(2)

Interpretation: RMSE penalises larger errors more than MAE, making it more sensitive to outliers. A smaller RMSE shows better predictive performance.

3. Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_{i-}\overline{y})^2} \quad \text{---------(3)}$$

$\bar{y}$= mean of observed values

Interpretation: R^2 measures how well the predicted values explain the variance in observed values. A value close to 1.0 indicates an excellent fit.

4. Water Supply – Demand Satisfaction Index

$$\text{WSDI} = \frac{\text{Harvested Rainwater}}{\text{ToTal Water Demand}}$$

Interpretation: This measures the percentage of demand satisfied by harvested rainwater. A value WSDI≥1WSDI 1WSDI≥1 indicates surplus, while WSDI<1WSDI < 1WSDI<1 indicates shortage.

5. Nash–Sutcliffe Efficiency (NSE)

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_{i-}\overline{y})^2} \quad \text{-------(4)}$$

Interpretation: NSE is commonly used in hydrology to evaluate water models. Values range from ∞- \infinity to 1, where NSE=1NSE=1NSE=1 indicates a perfect match between observed and predicted values.

IV. RESULTS AND DISCUSSION

4.1 RAINFALL ANALYSIS

Looking at the above analysis of the rainfall in Panther in the year 2017, it showcases the monthly rainfall pattern of the area, with the daily and monthly mean at a 95% confidence interval. The visualisation enabled us to observe that throughout the year, Panther generally has a substantial amount of rainfall. The monsoon season can be identified from the period of May till October, as it can be seen that there is a steady growth in terms of the monthly average of precipitation throughout this period.

Looking into the daily mean rainfall data, we observed that it is similar to the monthly rainfall pattern, as there is an increase throughout the monsoon season. Interestingly, we are also able to observe that there are days where there is a sudden peak in the amount of rainfall in Mid-July (about 780mm) and September (about 570mm), which surpassed the monthly average. Such a significant increase in rainfall could be an anomaly due to sudden heavy downpours or simply an error in data collection. Even so, we are able to determine that Panther in general, has a large amount of precipitation throughout the year. This further supports our decision to implement rainwater harvesting technology in the Panther location.

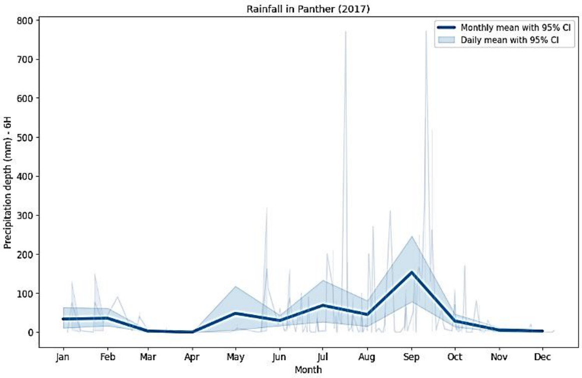


FIG. 8: RAINFALL IN PANTHER(2017)

4.2 Harvestable Rainwater

Using rooftop catchment area and runoff coefficient values, the total harvestable rainwater was estimated. The study found that the total annual harvestable water volume was litres, which can significantly contribute to meeting the building's water demand. However, spatial and temporal rainfall variability introduces uncertainty in the availability of harvested water.

4.3 Water consumption per square metre

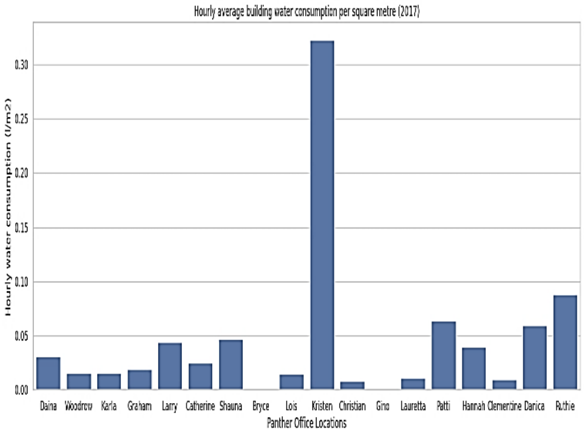


FIG 9: HOURLY AVERAGE BUILDING CONSUMPTION PER SQUARE METER(2017)

After finding out the positive correlation between the sqm of building and the water consumption, we would like to do a further analysis on the water consumption per sqm for the different office buildings. This analysis would allow us to have a better understanding on the water consumption rate of each building, regardless of their individual building size. For this segment, we would be using the 'sqm' feature from the metadata.csv dataset and the water.csv dataset for the year 2017. To achieve the water consumption per sqm, we used the total sqm of the building divided by the average hourly water consumption. The following will be the calculated average hourly water consumption/m2 :

4.4 Prediction Analysis

To have a more precise estimation of the rainwater harvested, we have decided to do a predictive analysis on the rainfall, using the air temperature data as mentioned in our AI Canvas, which is an important factor that influences the intensity of rainfall. This is because as the average temperature at the Earth's surface rises, more evaporation occurs, which, in turn, increases overall precipitation. Therefore, the air temperature data will be retrieved from the same dataset, in the weather.csv file.

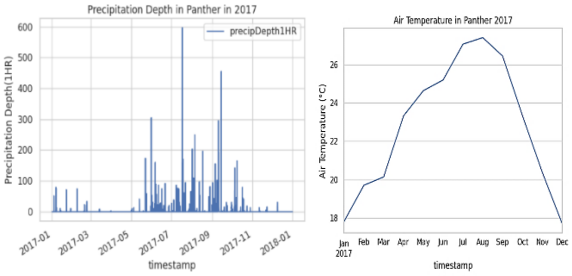


FIG. 10 PRECIPITATION DEPTH IN PANTHER AND AIR TEMPERATURE.

The data demonstrates a seasonal variation in air temperature across the year. In the early months (January–March), the temperature remains relatively low, fluctuating between 18°C and 20°C. From April onwards, there is a steady increase in temperature, with a notable rise between April and July, where the temperature peaks at around 27.5°C in August. After September, a sharp decline in temperature is observed, with values dropping rapidly from 26°C in October to around 18°C in December, marking the onset of the cooler season.

4.5 Prediction vs actual

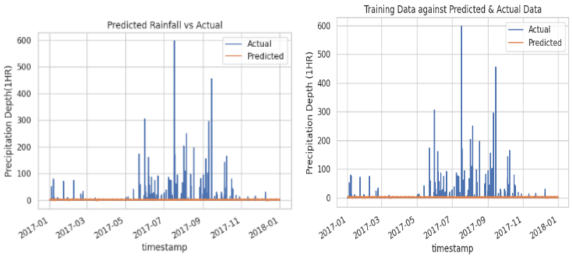


Fig. 11 predicted rainfall vs actual

4.6 Regression Evaluation Matrix

With the Mean Absolute Percentage Error being inf, we have decided to use the 3 other evaluation metrics, namely Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error, to evaluate the model. Mean Absolute Error (MAE) measures the average magnitude of the errors, it is the average of the absolute differences between the predicted and actual results Mean Squared Error (MSE) measures the error by calculating the average squared difference the predicted and actual values, a smaller value would indicate a better forecasting model Root Mean Squared Error (RMSE) is the standard deviation of the prediction errors, it is the square root of the average of squared differences between prediction and actual results, a smaller value would indicate a better forecasting model

Mean Absolute Error: 2.397739389437399
Mean Squared Error: 179.04157984832642

Root Mean Squared Error: 13.38064198192024
The Mean Absolute Error is 1.887, which indicates that the model is considerably acceptable. However, the high values of Mean Squared Error, being 140.150, and Root Mean Squared Error being 11.838, indicate that this prediction model is not preferred for prediction.
Overall, we would consider this prediction model not to be an accurate prediction that we can solely rely on due to several limitations and its accuracy after our evaluation.

4.6 Estimated Cost Saved

To determine the estimated annual cost saved by Miller Corporation through the implementation of rainwater harvesting technology, it can be calculated using the predicted rainfall in the following:
Annual Rainfall Collected = Catchment Area x Predicted Annual Rainfall
As the Kristen office building has a gross floor area of 8719.9 sqm, assumed to be 8 storeys high, each floor area would be 1089.99 sqm.
The catchment area is estimated to be about 30% of the available roof space. Hence, the catchment area for Kristen will be 326.99 sqm.
The volume of water collected from rainwater harvesting is: 3459.059814453125 m3
The cost of water saved is: $9477.82421875
Kristen Water Consumption in Cubic meters: 24472.4485254
Expected Water Collected from rainfall: 3459.059814453125

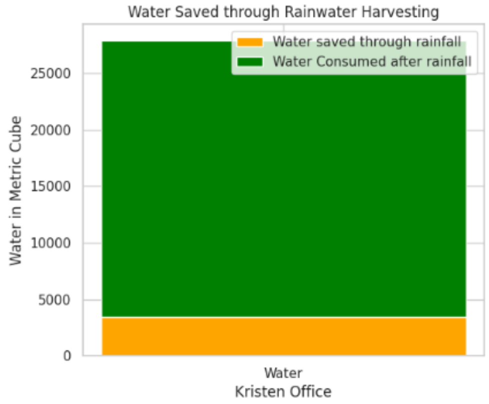


Fig.12 Water saved for cu

DISCUSSION

The study confirms that integrating rainwater harvesting with machine learning models improves decision-making by:

- Providing quantitative estimates of water savings potential.
- Identifying critical shortage periods where storage or backup supply is required.
- Supporting sustainable water management strategies for urban buildings.

However, limitations include data variability, assumptions regarding runoff coefficients, and exclusion of factors such as evaporation losses. Future research may incorporate deep learning models, climate change projections, and economic cost–benefit analysis to strengthen the framework.

V. CONCLUSION

According to our prediction analysis, we are able to derive that we would be able to save about 13.45% of the annual water consumption cost. This is below our target savings outcome, which was at least 20%. However, our prediction model was not considered to be entirely reliable due to its accuracy, and we believe that with more data collected in the future, we will have a more precise prediction of savings. In addition to that, despite the potential savings not hitting the intended outcome, our sustainable rainwater harvesting technology might still be recommended to be implemented in Panther. This is because it is still considered a sustainable and cost-effective
saving solution in the long run, and it will enable water conservation, which is crucial in Panther (Florida).

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