EVALUATION OF RAINFALL VARIABILITY AND RAINWATER HARVESTING FEASIBILITY IN KHULNA CITY THROUGH MACHINE LEARNING: A CASE STUDY

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ABSTRACT

Coastal regions are vulnerable when saline water intrusions threaten potable drinking water. Khulna city, one of the largest metropolises in the world and part of coastal Bangladesh, faces this same challenge as saline intrusions into waterways cause difficulties in the allocation of proper waterways to adequately distribute water throughout the city's needs. This study aims to evaluate the rainwater harvesting potential in Khulna, Bangladesh. To predict rainfall by weather parameter data and using future rainfall trends for predicting rainwater harvesting potential, Machine learning techniques were applied in order to assess future rainwater harvesting potential. For this research, trends of key weather parameters, such as temperature, cloud coverage, and humidity were analyzed and presented. Artificial Neural Network (ANN) and ANN-based time-series models (NARX) were used to predict future rainfall. Roof catchment areas for rainwater harvesting were measured using satellite imagery obtained from Google Earth Pro. The results from ANN and NARX training showed promising predictive capabilities, having good regression ($r = 0.87$ and 0.80 respectively), which indicate strong model performance. The combined spatial, as well as temporal datasets, facilitate aggregated results which indicate a fairly promising rainwater harvesting potential for three representative wards (ward 2, 11 and 23) of Khulna, with ward 2 exceeding the water requirement by a margin (21-97%) and ward 11 and 23 meeting a substantial water requirement amount (38-61% and 50-80% respectively). The consummate results of the proposed study would contribute to enhancing climate-resilient, as well as site-specific, water management mapping for future urbanization initiatives.

Keywords: *Rainwater Harvesting, Urban water supply, Machine Leaning, Safe Water Management, Rainfall Prediction*

1. INTRODUCTION

Water is essential for our survival, and access to clean water is a fundamental human right. However, in the twenty-first century, this right is becoming increasingly difficult to maintain as water shortage becomes more obvious due to overpopulation, uncontrolled development, and rapid climate change around the world. (Mishra, 2023).

Bangladesh, despite being known around the world for being a country of rivers, fertility, and heavy monsoon rainfalls, faces similar problem as a large portion of that rainfall occurs in monsoon seasons, leaving the rest of the year with extended dry periods (Shahid, 2009). In urban areas, rising populations and expanding settlements have gradually increased pressure on groundwater, creating significant stress on municipal water supply systems (Borah, 2025). Furthermore, continuous contamination of surface water has reduced the safe and reliable water source (Islam et al., 2000). Khulna City, along with the aforementioned problems, faces other unique water-related problems. It is located in the southern saline-prone coastal areas, making groundwater use more challenging due to saline infiltration in underground aquifers (Rabbani et al., 2013). In addition to seasonal water shortages, the poor quality of the existing supply creates water shortage problems for the local population on a daily basis (Rabbani et al., 2013). All of these situations make it apparent to explore alternative and supplementary water resources. For some time, Rooftop Rain Water Harvesting (RRWH) has gained popularity as an alternative, practical, sustainable, and locally adaptable solution that provides clean, low-cost water and can take care of rising water demands. (De Sá Silva et al., 2021).

There have been multiple studies on the application of rainwater harvesting in other major districts (i.e. Dhaka, Rajshahi) (Bashar et al., 2018), but there has been little research on the implications of RRWH on Khulna city (Chakrabarty & Mohiuddin, 2024). Furthermore, limited research has been done implementing analytical tools like machine learning modeling (ANN, NARX) to evaluate rainfall and harvesting capacity. Khulna, due to generally being a densely built area, the city's rooftop areas provide ideal conditions for rooftop rainwater collection, which could serve as a reliable alternative to traditional water supply systems. However, accurate RRWH potential depends on reliable rainfall predictions. Machine learning modeling, more specifically, Artificial Neural Network (ANN), is used in this regard to predict rainfall from weather parameters (Nanda et al., 2013). Nonlinear Autoregressive Network with Exogenous Input (NARX) is also used in this regard, mainly to forecast rainfall to design rainfall distribution and storage systems accordingly (Mishra et al., 2018).

The objective of the study is to evaluate the feasibility of RRWH in selected areas of Khulna City by determining rooftop catchment areas and analyzing rainfall conditions by the use of machine learning modeling, integrating rainfall data, catchment area measurements, and runoff coefficients for accurate feasibility assessment. The goal of this study is to determine the capability of rainwater harvesting and draw attention to its importance in reducing usable water shortage crisis. In the future, it may also contribute to a bigger goal of creating water-resilient cities in Bangladesh in the face of mounting scarcity.

2. METHODOLOGY

2.1. Study Area

The study area for this research is selected Khulna City Corporation, specifically Ward 2, 11, and 23 (Figure 1), which is located in the southwestern part of Bangladesh and nearest to the Bay of Bengal, at 22.817° N, 89.550° E. The area of Khulna city corporation is 45.65 km^2 and is approximately 9m above mean sea level (Bangladesh Statistics, 2019). According to weather parameter evaluation, Khulna’s heavy rainfall occurs in May to July, and the lowest month is in January to March (Climate Risk Country Profile - Bangladesh). The groundwater and surface water of Khulna are strongly influenced by salinity due to being near of coastal area. Khulna City Corporation comprises 31 wards. The population in the urban area is about 719 thousand residents (Population and Housing Census, 2022).

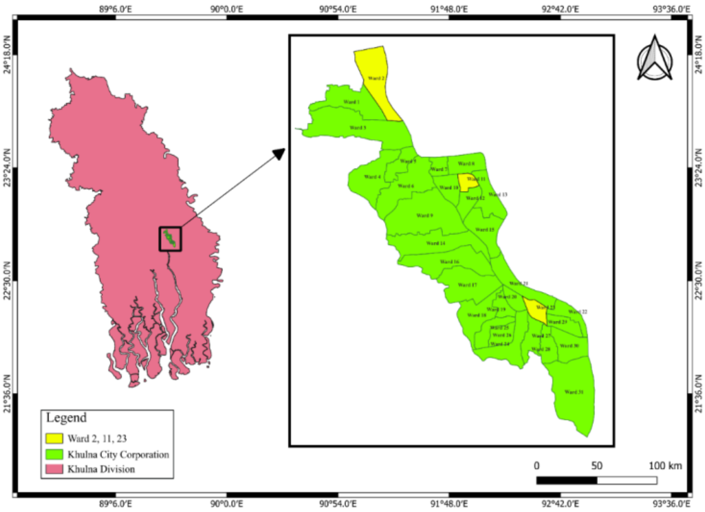


Figure 1: Geographic Location of Study Area (Khulna City Corporation)

2.2. Research Framework

The entire methodological framework used in this study is presented in Figure 2. The approach encompasses the use of weather data, in addition to ANN model development for rainfall prediction assessment and ultimately Rainwater Catchment Potential & Feasibility. The graphical flowchart represents data acquisition, preprocessing, model development, and analysis.

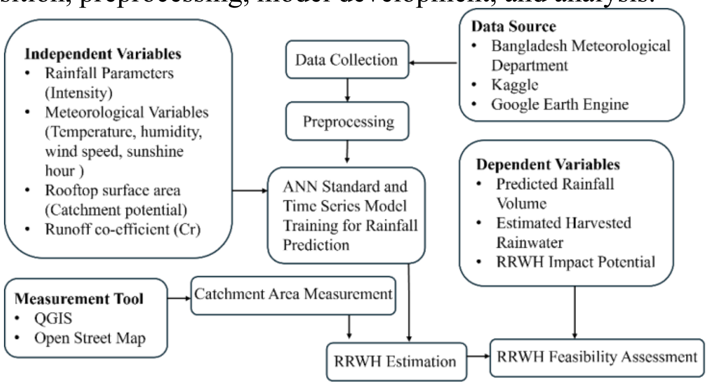


Figure 2: Flow Chart of Study Framework

2.3. ANN Model Structure

Artificial Neural Networks (ANNs) are computational algorithms modeled after the processes of the human brain, designed to recognize patterns, approximate functions, and predict the behavior of data (Nanda et al., 2013). By using the ANN tool of MATLAB 2019a, the monthly rainfall of Khulna was predicted, where the input variables were year, month, maximum temperature (ºC), minimum temperature (ºC), cloud coverage (octa), sunshine (hours), wind velocity (m/s), and relative humidity (%). The structure of the ANN model is used (8-5-1-1) as shown in Figure 3. The basic operation of a single artificial neuron can be expressed mathematically. For a neuron with x_n, weight w_n, and bias term b, the neuron first computes a weighted sum as demonstrated in Equation 1.

$$z = \sum_{i=1}^{n} w^i x^i + b \tag{1}$$

$$y = f(z) = f\left(\sum_{i=1}^{n} w^i x^i + b\right) \tag{2}$$

From Equation 1, z is then passed through a non-linear activation function f(z) to introduce non-linearity into the model, yielding the output of the neuron, shown in Equation 2.

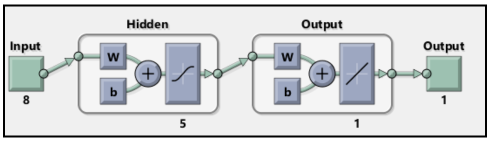


Figure 3: ANN Structural Diagram

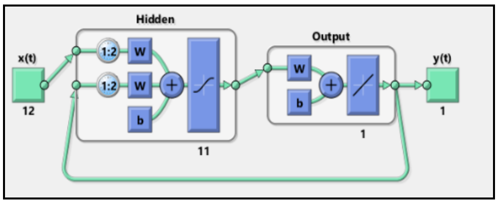
The ANN model was designed by using 8 different weather parameters as input and known rainfall data as output. 300 datasets were used in the process of designing the model, where 210 datasets were used for training purposes (From 2000 to 2024), which were split into 70% for training, 15% for testing, and 15% for validation. The remaining 90 datasets were reserved for independent performance analysis.

2.4. Time Series Analysis by ANN (NARX)

The Nonlinear Autoregressive with Exogenous Input (NARX) of the ANN model is a powerful tool for time series prediction as it can aid in creating strong nonlinear and dynamic relationships without any prior assumptions about the data; rather, the network learns from the data through adjusting weights by training, minimizing errors for prediction (Shao et al., 2022). In the time series analysis of ANN, the dataset was formed in a way mostly known as the 'Sliding Window Method' (Vafaeipour et al., 2014), where, previous 12 months of rainfall data were input variables, and the output variable is the 13th month, as shown in Figure 4a. As the window moves forward, new input-output batches are formed. This form of data sequencing helps train the ANN to predict future values based on past trends. Both ANN and ANN(NARX) work in parallel in this study. Based on the ANN model, rainfall was predicted using various meteorological parameters, and the ANN (NARX) model then utilized this predicted data to forecast future rainfall for assessing potential rainwater harvesting opportunities.

Input					Output
M_1	M_2	M_3	…..	M_{12}	M_{13}
M_2	M_3	M_4	…..	M_{13}	M_{14}
M_3	M_4	M_5	…..	M_{14}	M_{15}
…..	….	….	…..	….	….
M_{278}	M_{279}	M_{280}	…..	M_{288}	M_{289}
M_{279}	M_{280}	M_{281}	…..	M_{289}	M_{290}

(a)



(b)

Figure 4: ANN Time Series, (a) Sliding Window Data Formation; (b) NARX Structure

The NARX model uses previous values (x_t) to determine next values (y_t), which then loops back and also acts as additional input to help the network learn temporal dependencies, making it more effective in predicting sequential data (Figure 4b). NARX operation procedures can be described mathematically in Equation 3.

$$\boldsymbol{y(t) = f(y(M-1), y(M-2), \ldots, y(M-d_y), x(M-1), x(M-2), \ldots, x(M-d_x))} \tag{3}$$

Whereas, $y(M)$ is the target/output variable (e.g., rainfall),$x(M)$: input/external variable(s), d_y, d_u: number of past delays, and $f(\cdot)$: nonlinear function estimated by the neural network.

The ANN (NARX) time series model was designed by creating a sliding window dataset from rainfall data of 300 months (From 2000 to 2024). The dataset was then divided into 2 parts: 12 columns of 12 months of rainfall data, which was taken as input, and 1 column of 13th months of rainfall data, which was taken as output. The dataset was divided into 70% training, 15% validation, and 15% testing.

2.5. Model Validation

For this study, some statistical analyses were made in order to validate the performance of the designed models. Along with the coefficient of correlation(R^2), other statistical parameters were determined, like Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Deviation (MAD), which can be determined by equations 4, 5, 6, and 7, respectively. These parameters were selected as they were used in various similar research as proven methods of understanding the effectiveness of a model's prediction capabilities (El-Shahat et al., 2024). For the Coefficient of Correlation, a value of 0 indicates the model has no relation, and -1 and +1 indicate positive and negative higher relation with the actual result. For MSE, RMSE, and MAD, a lower value indicates less error in the designed model, acting as a representative of its effectiveness. The formula for the statistical parameter determination is as follows:

$$r = \frac{n(\sum C_i P_i) - (\sum C_i)(\sum P_i)}{\sqrt{[n\sum C_i^2 - \sum(C_i)^2][n\sum P_i^2 - \sum(P_i)^2]}} \tag{4}$$

$$\text{MSE} = \frac{\sum_{i=1}^{n}(C_i - P_i)^2}{n} \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(C_i - P_i)^2}{n}} \tag{6}$$

$$\text{MAD} = \frac{\sum_{i=1}^{n}|C_i - P_i|}{n} \tag{7}$$

Where C_i is the Actual Rainfall Value in mm, and P_i is the Predicted Rainfall Value in mm.

2.6. Area Calculation for Rainfall Harvesting

For this study, the area was selected to be wards 2, 11, and 23 of Khulna City Corporation, primarily, as they are situated in 3 separate locations of Khulna City. Key components (i.e., area, roof pattern) are calculated by utilizing QGIS and the Open Street Map (OSM). OSM map of Bangladesh was imported to QGIS, and OSM data of the roof shapes from the map was downloaded and later generated as a polygon shapefile. Since rooftops in Khulna comprise concrete and tin roofs, a thorough cross-referencing of the generated shapefile with the Google Earth map was done to distinguish tin roofs from concrete roofs.

2.7. Harvestable Rainwater Calculation

Implementation of the rainwater harvesting system is reliant on the amount of potential harvestable rainwater (Rozaki et al., 2017). Rainwater harvesting is illustrated as an important part of this study, as Khulna's groundwater is not suitable for drinking or domestic use due to its high salinity. Using the data collected from the catchment area calculations and the rainfall data from (ANN to ANN (NARX)) machine learning model, the rainwater harvesting capability was determined by the Rooftop Catchment Method (Gould and Nissan, 1999). Equation 8 is used for the RWH is Equation 8.

$$S = A \times R \times C_r \tag{8}$$

Where S is the rainwater harvesting Potential, a is the catchment Area, R denotes Mean Rainfall for a specific period, and C_r is the Coefficient of Runoff. The coefficient was used for the rainwater harvesting as a tin roof: 0.8, and a concrete roof: 0.7 (Biswas & Mandal, 2014).

2.8. RRWH Impact Assessment

According to a survey conducted by Khulna Water Supply Project in 2024, the average water consumption in Khulna is 73 lpcd (Asian Development Bank, 2019). By integrating this data with the population survey in 2022 (CityPopulation.de, 2022), an estimation of water consumption in each ward per month was made. This data was then compared with RRWH data from 2020-2024 to evaluate how much of the water consumption can be affected by RRWH.

3. RESULT & DISCUSSION

3.1. Weather Parameter Analysis

Using the present weather parameter data obtained from the Bangladesh Meteorological Department (BMD), an overall analysis of different weather parameters of Khulna from 2000 to 2024 was done to better understand weather trend changes over the past two decades.

The trend of weather parameters is illustrated in Figure 5, where minimum temperature decreases by about 30% over the past decade, and the maximum temperature increased by about 7-10% over the past few years. Although cloud coverage and relative humidity remained similar over twenty years, wind velocity has increased dramatically (about 200%) with seasonal fluctuations. Rainfall has been relatively the same, with some seasonal exceptions.

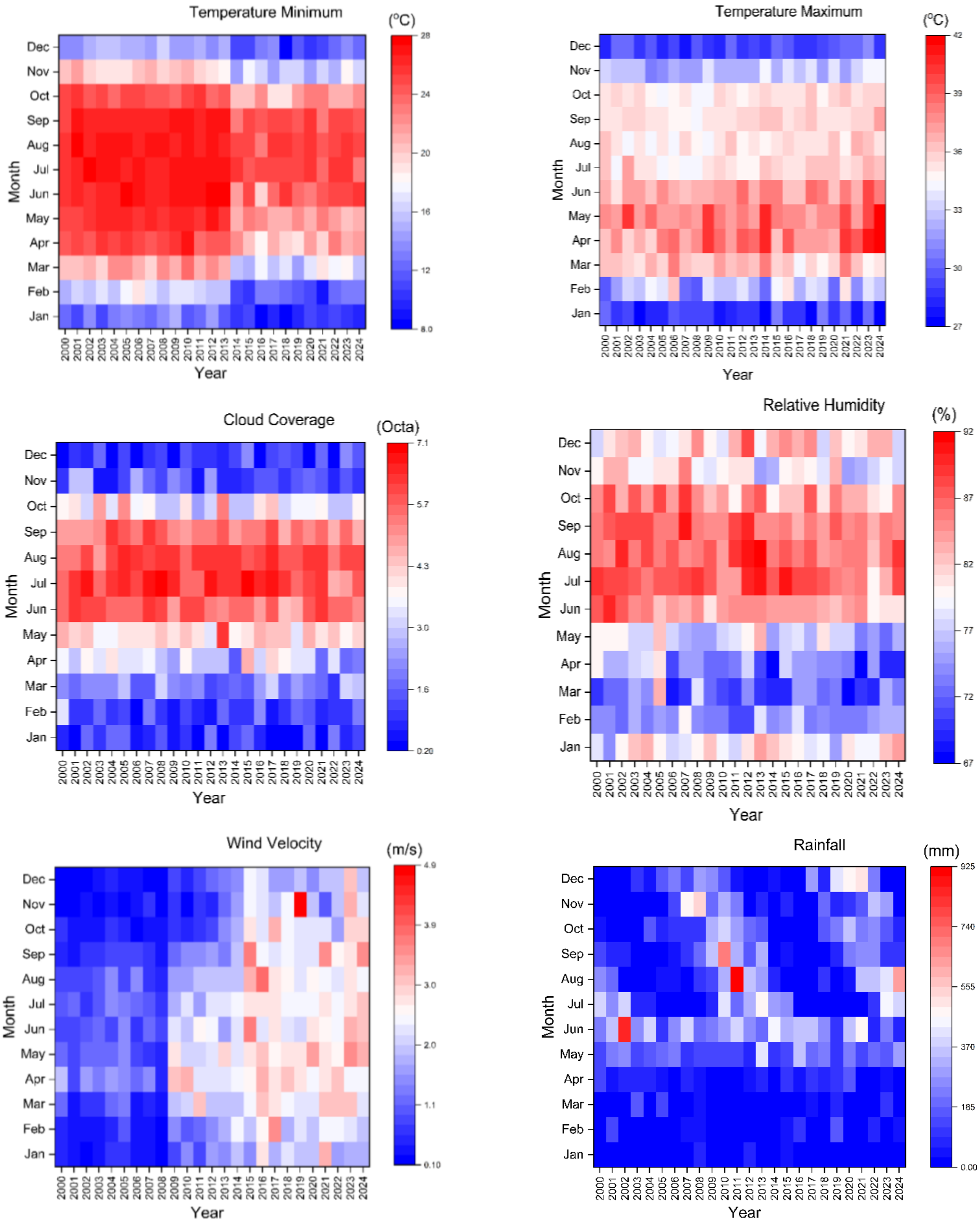
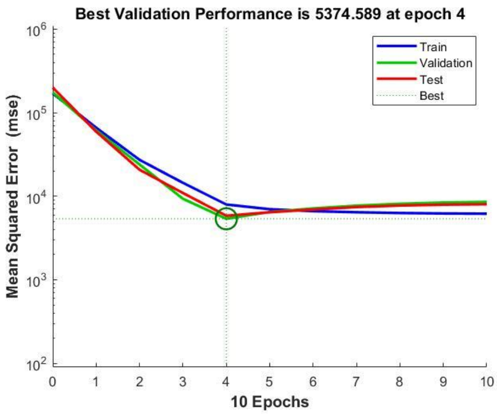


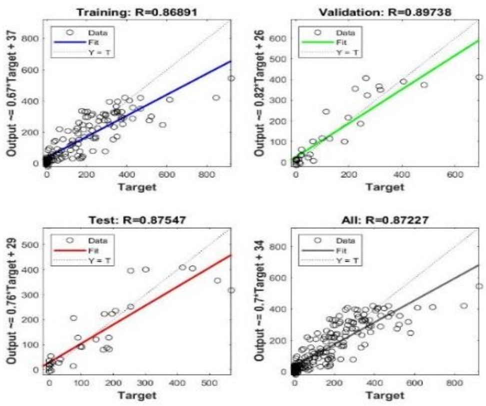
Figure 5: Weather Parameter Graph (2000-2024)

3.2. ANN Model Results

The model was trained with 1-30 hidden layers; the best validation performance was 5374 at 5 hidden layers (Figure 6a). The regression analysis for the ANN model performed for training 0.87, validation 0.89, testing 0.87, and overall, 0.87 as shown in Figure 6b. The error histogram of the model indicated that most errors occurred near zero. The narrow symmetric distribution around zero indicates the model generalizes well with good accuracy and minimal large deviations. Training performance results show the changes of gradient, mu, and validation checks improved over 10 epochs. The gradient steadily decreased, indicating convergence of the learning process. On the other hand, mu and validation checks increased, suggesting the model stopped training as performance on the validation state stopped improving. These results indicate strong accuracy of predicted rainfall based on weather parameters.



(a)

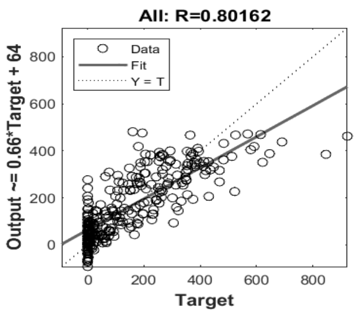


(b)

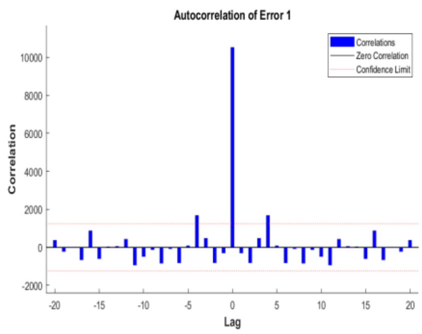
Figure 6: (a)Performance and (b)Regression Results of Neuron 5 Model Training

3.3. ANN (NARX) Time Series Result

After numerous trials and errors, the optimal combination of neurons and delays was determined to be 11 neurons and 2 delays, achieving a performance of 7629, while testing 1 to 15 hidden layers. The overall regression of the model found 0.8, as illustrated in Figure 7a. As shown in Figure 7b, the model exhibits strong self-correlation due to a massive spike at lag 0, which is expected since each error perfectly correlates with itself. All other lags are within the confidence limit, overall indicating independent and random distribution of the model's prediction errors, indicating a good model fit. Figure 7c shows high prediction accuracy over all data phases. The lower panel displays a small and randomly distributed error plot, indicating a good model generalization and low bias. These results indicate fairly accurate prediction of future rainfall based on present rainfall data.



(a)



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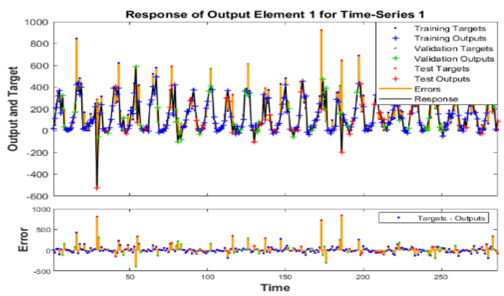


(c)

Figure 7: (a)Regression, (b)Autocorrelation of Error, and (c)Time Series Output Response Plot of Neuron 11

3.4. Performance and Validation of Model

To determine the testing performance of the ANN model at neuron 5, a thorough analysis was conducted using the remaining 90 independent datasets, and the corresponding performance metrics were evaluated based on the statistical analysis parameters described in model validation. After the performance analysis, it was identified that the model with 5 hidden neurons performed very well with significant Coefficient of Correlation (R = 0.89), Coefficient of Determination (R^2 = 0.793) (Figure 8a), meaning there is an 89% similarity between predicted rainfall and actual rainfall, and the model can explain 79% of the outcome variability. The model also had low error values (RMSE = 74.9, MSE = 5610.29, MAD = 50.26). The performance analysis suggests that the ANN model shows strong accuracy, stability, and generalization, making it reliable for practical predictive usage.

Testing the NARX time series model against actual rainfall from November 2023 to December 2024 provided a Correlation coefficient of 0.86 and Determination Coefficient of 0.73 (Figure 8b), meaning there is an 86% similarity between predicted rainfall and actual rainfall, and the model can explain 73% of the outcome variability. This value could have been improved, but due to some months having zero rainfall, the quality of the sequence was a bit inferior during the training phase. Despite that, a 0.86 correlation coefficient indicates a relatively strong model structure, which can be used for practical life future rainfall prediction. Comparison between actual and predicted rainfall for both the ANN and NARX models is illustrated in Figure 8c and Figure 8d, respectively.

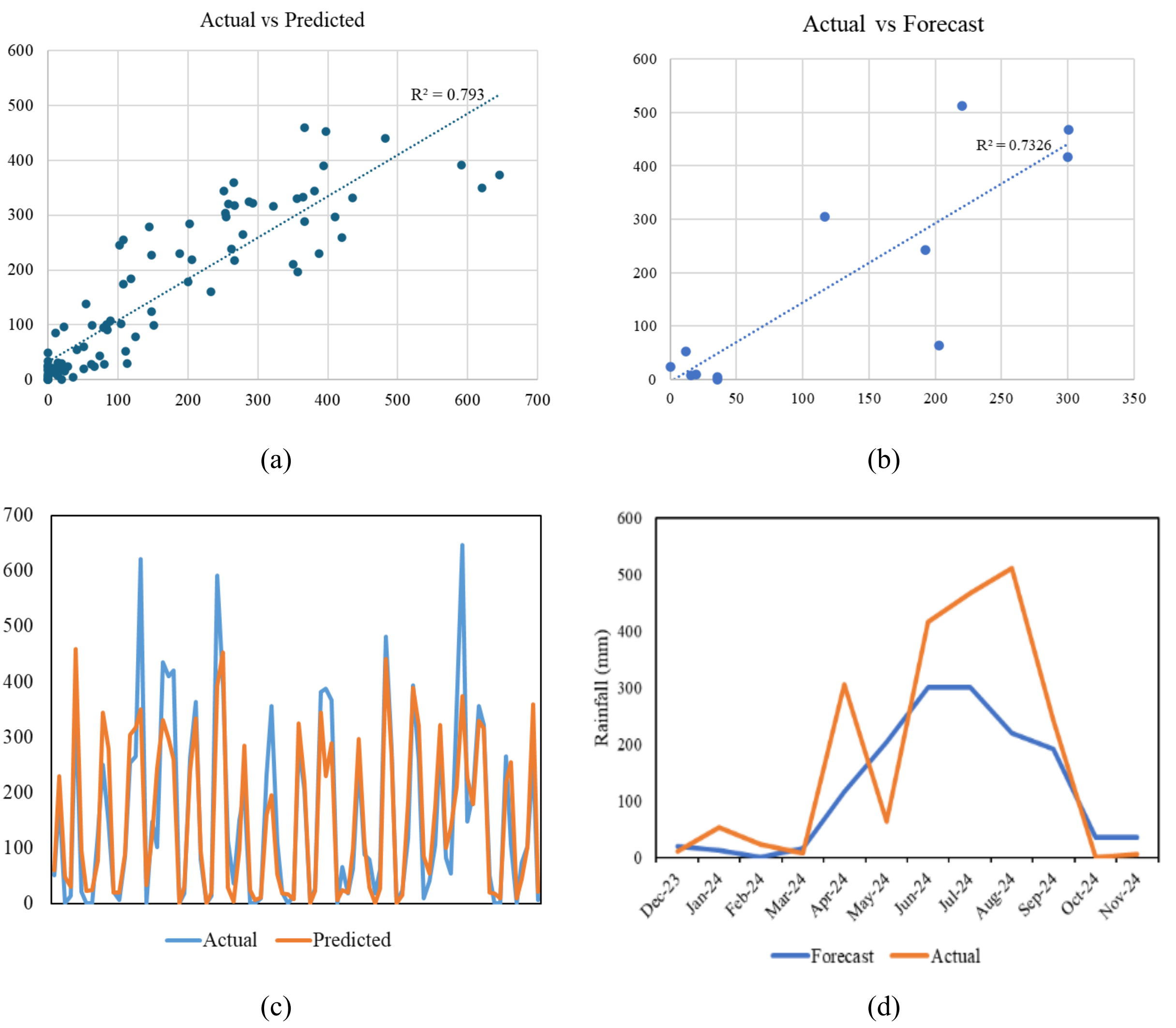


Figure 8: Correlation of (a) ANN, (b) ANN (NARX); Comparison of Actual with predicted/forecasted (c) ANN, (b) ANN (NARX)

3.5. RRWH Result

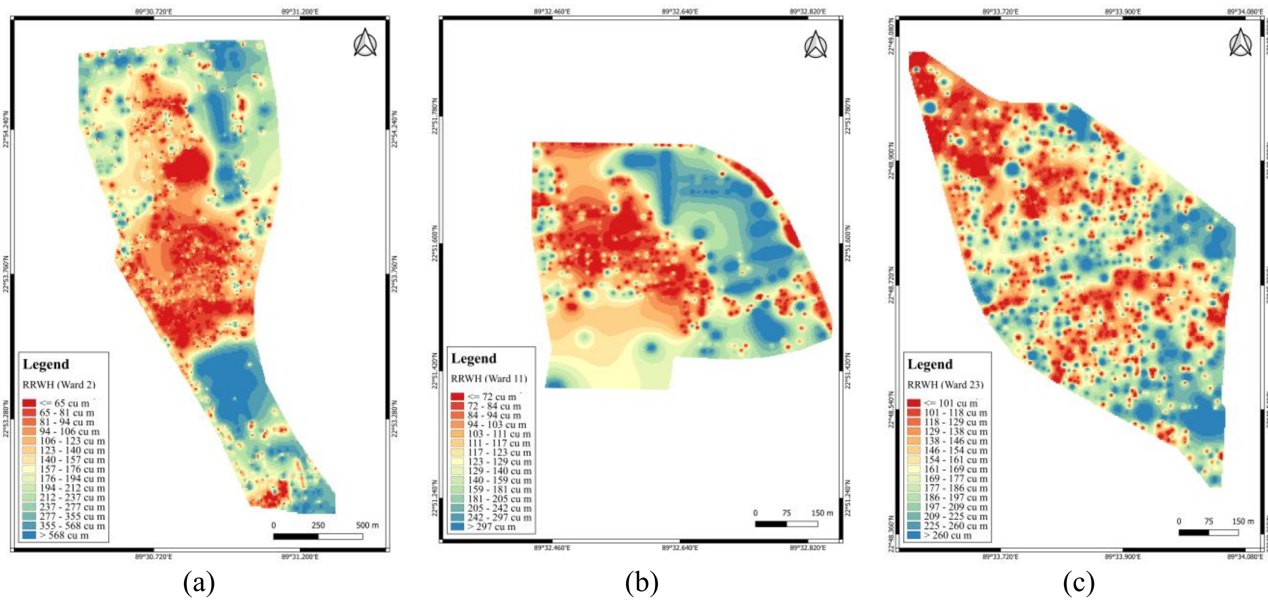
Using integrated measurement of area by QGIS, the area of the plotted rooftop polygons of each of the 3 wards was calculated for an estimation of the overall catchment area available in that area, as shown in Figure 9. The total area of the tin roof was found 194902 m^2, 19078 m^2, 23375 m^2, and concrete roof 190050 m^2, 61071 m^2, 154931 m^2, in word 2,11, and 23, respectively.

(a) (b) (c)

Figure 9: Measured Tin and Concrete Roof Area in Ward 2(a),11(b), and 23(c)

Due to cross-referencing the OSM map in QGIS with a satellite image of Khulna City Corporation, tin and concrete roof structures were distinguished beforehand, making it easier to evaluate the harvestable amount of rainwater by tin and concrete catchment areas separately. This lead to a proper evaluation of RRWH of tin and concrete catchment areas of the 3 wards.

Spatial Contour maps were generated from the summation of area calculated from QGIS and rainfall data of 5 years (2020-2024) to better understand spatial variation across the wards, highlighting higher accumulation zones in blue and low potential areas as red (Figure 10).



(a) (b) (c)

Figure 10: RRWH Spatial Variation Contour Map of Ward 2(a),11(b), and 23(c)

Temporal Contour maps were also generated that gave a clear idea of the difference in water harvesting capabilities of each ward over the years (Figure 11).

Area calculations illustrated in Figure 9 indicate that, the percentage of roof area in ward 2 is nearly the same (49.37% tin roof, 50.63% concrete roof). In comparison, the roof area in ward 11 (23.8% tin roof, 76.8% concrete roof) and ward 23 (13.11% tin roof, 86.89% concrete roof) shows a dominance of concrete roofing, reflecting a shift toward more permanent construction materials in these wards. This result also relates to the RRWH capabilities of each ward based on roof types. As shown on the contour maps in Figure 11, the highest rainfall during 2020-2024 occurred during August-September 2024. During that period, the harvestable water volume in Ward 2 would be 147,945.79 m³, with 53.96% originating from tin roof catchment areas and 46.04% from concrete roof catchment areas. This aligns with the percentage of catchment areas in Ward 2. Similarly, Ward 11 (29702.47 m³ total, 26.31% from tin roof, 73.61% from concrete roof) and Ward 23 (65101.69 m³ total, 14.71% from tin roof, 85.29% from concrete roof) display comparable trends.

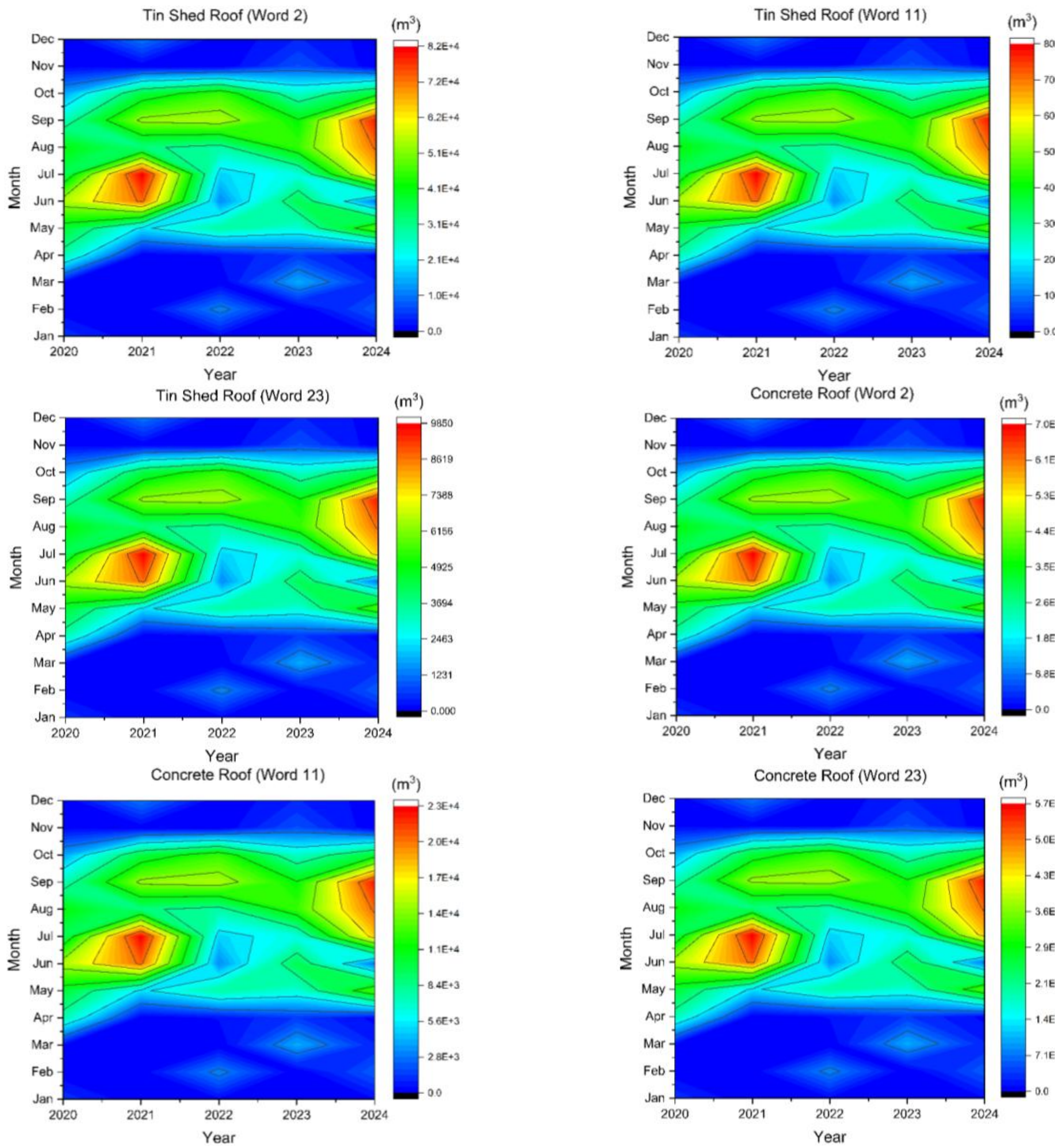


Figure 11: Contour Graph of RRWH by Tin and Concrete Roof of Ward 2, 11 & 23

3.6. RRWH Impact

For better evaluation of RRWH impact, the result of the comparison between RRWH and water usage was plotted in a graph, shown in Figure 12. From the graph, a general idea of the impact of RRWH on water consumption for the population of wards 2, 11 and 23 can be seen. For Ward 2, RRWH can 6easily exceed the water requirement by 21-97% and store the surplus water for distribution to other wards or future use. For Ward 11, RRWH can mitigate about 38-61% for water demand. For Ward 23, RRWH can help reduce Water requirement by around 50-80%. Though it is based on data from 2020-2024, and so these values are not absolute, a general idea of expectation from RRWH can be understood. Even though water demands can not be fully met by RRWH in wards 11 and 23, it can be mitigated by half or more, which in itself is a huge development. Furthermore, excess water stored by other wards can also help reduce water demand even more for these wards.

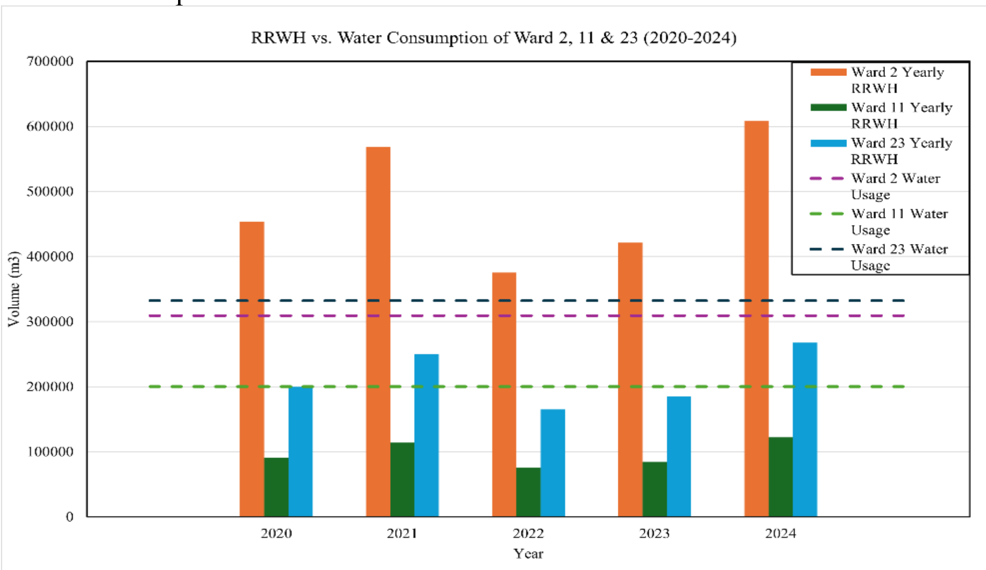


Figure 12: RRWH vs. Water Consumption Graph

4. CONCLUSION

Results from this study reveal that RRWH potential in Khulna is high and it can potentially mitigate municipal and groundwater dependencies by a margin with proper infrastructure and maintainance. With proper distribution system among wards, excess water can be distributed to neighboring wards, improving towards negating groundwater dependency altogether.This study also illuminates the potential of using ANN and NARX model to predict future rainfall and design possible storage and distribution systems according to projected changes in future rainfall trends. This study, thus, strongly advocates the necessity of a sustainable RRWH collection, distribution and storage system to meet the present and future water resource requirements of Khulna, with promising RRWH prediction for water usage and storage planning. Addition of a proper RRWH system with municipal water distribution system can be a key advancement in the direction of water crisis mitigation. Government initiative, support and campaign is also necessary for encouraging and helping the general populus in converting to RRWH systems and being more water efficient.

5. AI Declaration:

The authors declare that no AI tools were used for conducting this research.

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