Predictive Modeling of Marikina River Water Levels Along the Sto. Niño and Montalban Gauging Stations Using Artificial Neural Networks

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Outline

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Background of the Study

Flooding is a persistent issue, especially in Marikina.

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- Climate change and urbanization have increased the frequency and intensity of flooding (Agonafir, et al. 2023).
- Improper land use has also contributed to more frequent severe flooding in the Marikina River Basin (MRB) (Monjardin, et al. 2019).

Flooding is a persistent issue, especially in Marikina.

Figure 1: Marikina River, Source: Philippine Star

- In 2024, Typhoon Carina brought heavy rainfall causing the water level to reach 18.3 m and forcing residents to evacuate (Caliwan, 2024).

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- A system that has been developed is the flood forecasting and early warning system (Williams, M. Arguillas, and F. Arguillas, 2020).
- Currently, Marikina City employs an alarm level system using the water level under Sto. Niño bridge (Serafica, 2017).
- However, improvements to this system can still be made through early water level predictions.

More advanced flood forecasting utilizes two methodologies.

Physical Models

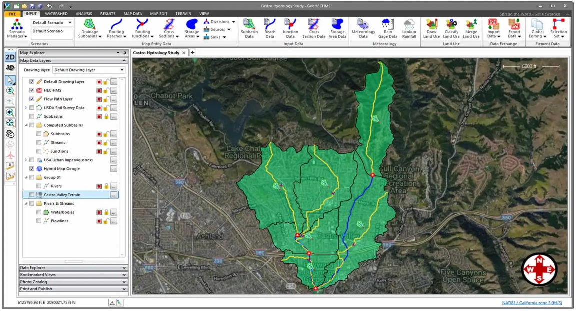

Figure 2: Software from Hydrologic Engineering Center 2024.

- These numerically solve water flow equations using different numerical techniques (Jain, et al. 2018).

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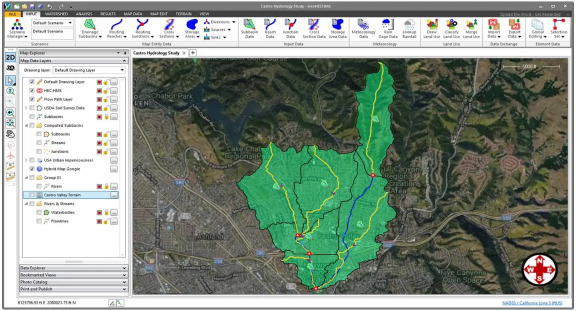

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- However, they are highly dependent on the availability of data for the physical parameters.

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Data-driven Models

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- These utilize machine learning, particularly, neural networks to analyze different datasets.
- However, these models do not know physical laws.
- Instead, patterns and trends between the input and output data are identified and used in predictions.

Objectives

This study uses ANN for water level prediction in the MRB.

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- determine if ANNs are better forecasting models of the MRB water levels than basic time series models,
- determine if adding more input features and changing lag values will improve the forecasting models, and
- provide recommendations and insights to stakeholders.

Scope and Limitations

The scope of our study is the Marikina River Basin (MRB).

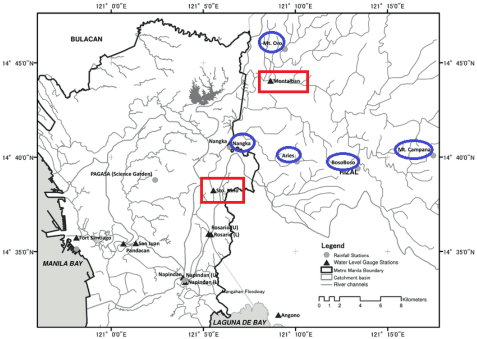

Figure 2: Marikina River Basin map; in red rectangles are the water level stations and in blue circles are the rainfall stations of interest.

Key Water Level Stations: Sto. Niño and Montalban station

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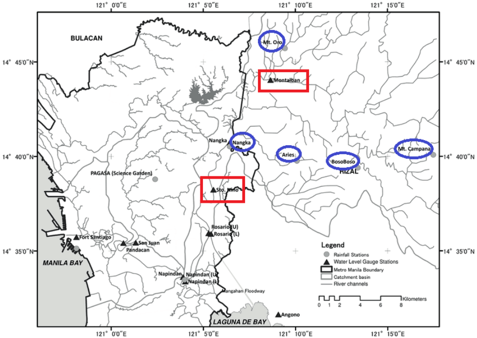

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Rainfall Stations: Boso-Boso, Mt. Aries, Mt. Campana, Mt. Oro, Nangka

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- They are not the only rainfall stations around the MRB.
- The stations were determined based on previous research in the area by Badilla (2008) and Santillan, et al. (2013) and current warnings provided by the Marikina Public Information Office.
- According to the Granger Causality Test, the rainfall data from these five stations have predictive capabilities for the water level at Sto. Niño.

Outline

Physical Models

Santillan, et al. (2013) used physical models to forecast discharge along the MRB.

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- Santillan, et al. (2013) used two flood modeling software – HEC HMS and HEC RAS to model discharge of historical flood events in the MRB.
- They used the Nash Sutcliffe Efficiency (NSE) which is a commonly used metric for assessing hydrologic model performance. It is given by:

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{N}(d_i - y_i)^2}{\sum_{i=1}^{N}\left(d_i - \overline{\overline{d}}\right)^2}$$

where d_i are the actual values, y_i are the predictions, and $\overline{\overline{d}}$ is the mean of the actual values.

Santillan, et al. (2013) used physical models to forecast discharge along the MRB.

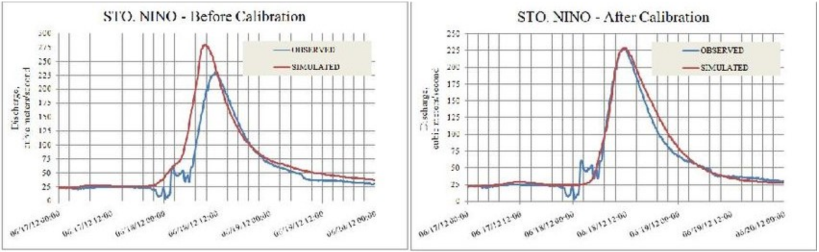

Figure 3: Discharge hydrographs from Santillan, et al.; model performance improved after some calibration.

- Their study achieved an NSE between 0.77 to 0.88 in simulating discharge along the MRB.

Badilla also used physical models to predict water level in the MRB.

Physical Models

- Badilla (2008) also made a flood model for MRB using the HBV model and DUFLOW.

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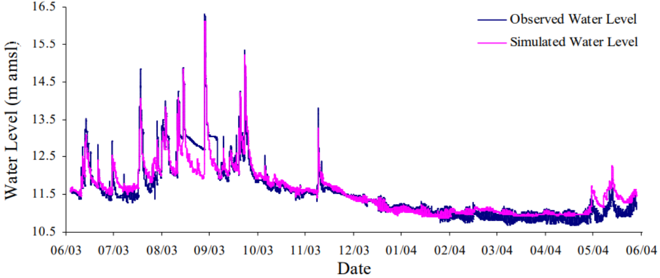

Figure 4: Water level predictions from Badilla; underestimations are observed in the earlier predictions while overestimations in the latter.

- Their model achieved an NSE of 0.9 but there were still differences between the predicted and observed values.

Data-Driven Models

DNNs can be optimized for hydrologic modeling.

- For instance, Dtissibe, et al. (2020) utilized DNNs to predict discharge along the Gardon d'Anduze River in France.

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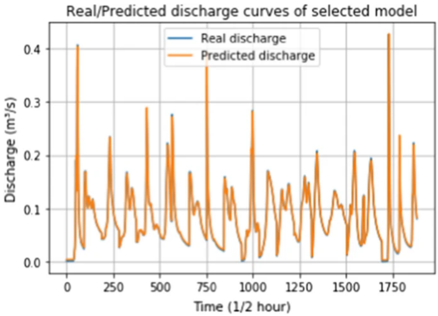

Figure 5: Discharge hydrograph from Dtissibe, et al.; their model predicted accurately with only a few underestimations.

- Their selected DNN achieved a very high NSE of 0.98

CNNs can also be used for sequential data.

- For instance, Wunsch, et al. (2021) aimed to forecast groundwater level in central Europe using different models.

CNNs can also be used for sequential data.

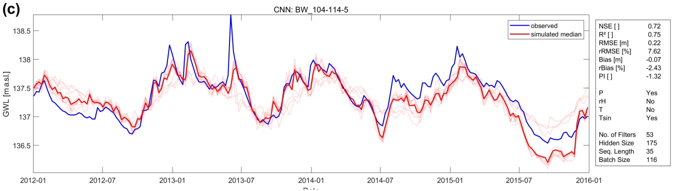

Figure 6: Groundwater Level Predictions from Wunsch, et al.; the predictions generally underestimated groundwater level by less than a meter, particularly the peaks.

- Using precipitation, temperature, and relative humidity, the CNN achieved an NSE of 0.72 at a faster computation speed.

LSTMs are most suitable for time series forecasting.

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- As an improvement over the standard RNNs, LSTMs have more complex information flow mechanisms.

LSTMs are most suitable for time series forecasting.

- As such, Ibañez, et al. used LSTM networks for reservoir water level forecasting in Angat Dam (2022).

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- As such, Ibañez, et al. used LSTM networks for reservoir water level forecasting in Angat Dam (2022).
- It was trained on 20 years of historical water level, rainfall, climate, and irrigation data.

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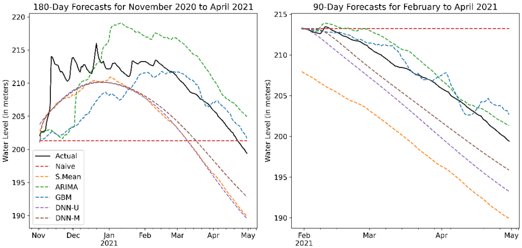

Figure 7: Angat Dam water level predictions from Ibañez, et al.; the LSTMs significantly underestimate water level.

- They claimed that LSTM networks were the best-performing models in both short and long-term predictions.

Outline

Data Collection and Pre-processing

Data was collected from the MMDA.

Data Sources

- The Effective Flood Control Operation System (EFCOS) of MMDA collects rainfall and water level data along key stations in the MRB.

The data went through preprocessing and engineering.

Steps

1. First, hourly rainfall and water level data per month for each station were compiled into single files per year.

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1. First, hourly rainfall and water level data per month for each station were compiled into single files per year.
2. Then, missing rainfall and water level data was filled in using linear interpolation.

Snippet of the final dataset.

Table 1: First 3 columns with the Sto. Niño water level data.

index	datetime	Waterlevel_Sto_Niño
0	2016-01-01 00:00:00	12.18
1	2016-01-01 01:00:00	12.19
2	2016-01-01 02:00:00	12.19

Table 2: Last 5 columns with the rainfall data from the 5 stations.

Aries	Boso	Campana	Nangka	Oro
0	1	2	0	0
0	1	1	1	0
1	1	1	0	1

Data was split 50% – 25% – 25% to account for seasonality.

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- Then, the 2017 data was equally split into the validation and testing sets.
- This was chosen to ensure a sufficient sample size for the rainy season in the Philippines.

Basic Time Series Modeling

Basic time series models were used as baseline models.

- Besides the models by Badilla (2008) and Santillan, et al. (2013), there are no other recent water level forecasting studies along the MRB.

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- Besides the models by Badilla (2008) and Santillan, et al. (2013), there are no other recent water level forecasting studies along the MRB.
- Thus, basic time series models using only the Sto. Niño water level values will be used to forecast the subsequent water levels.

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- Here, the basic time series models to be used are the autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models.

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- Here, the basic time series models to be used are the autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models.
- Afterwards, they were combined with the basic volatility models autoregressive conditionally heteroscedastic (ARCH) and generalized ARCH (GARCH).

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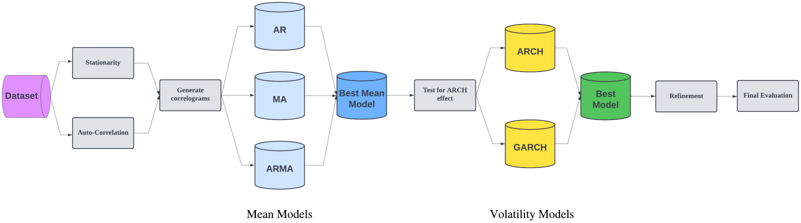

Figure 8: Processes for the basic time series modeling.

Neural Network Modeling

Three types of ANNs were used.

1. **Dense Neural Network**

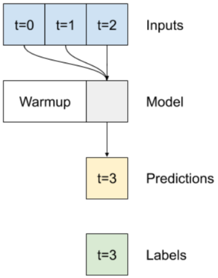

Figure 9: Dense Neural Network from TensorFlow 2024

- DNN flattens the two-dimensional input to follow the typical input shape of neural networks.

Three types of ANNs were used.

2. **Recurrent Neural Network**

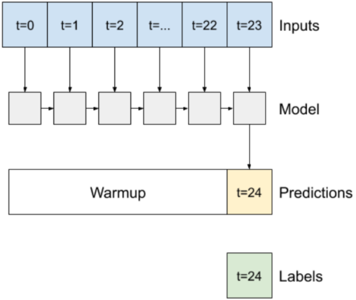

Figure 10: Recurrent Neural Network from TensorFlow 2024

- An RNN takes the state of the model after previous time steps into consideration by utilizing its gate mechanisms.

Three types of ANNs were used.

3. **Convolutional Neural Network**

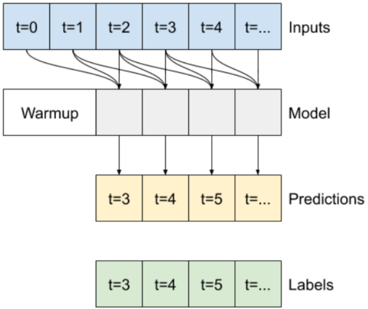

Figure 11: Convolutional Neural Network from TensorFlow 2024

- A CNN uses convolutional kernels to detect patterns across multiple time steps.

The general architecture for all three ANNs are similar

Model Architecture

- **DNN**: 3 hidden layers
- **RNN**: 1 LSTM layer and 2 hidden layers
- **CNN**: 1 1-D convolutional layer and 2 hidden layers
- 64 neurons per layer
- ReLU activation function for all layers

Time series forecasting is integrated into the neural networks.

WindowGenerator

- From TensorFlow, a data window was created to allow the ANN to take inputs from consecutive time steps together to make predictions.

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WindowGenerator

- **Input Width** is a parameter that determines the number of consecutive data points to use as input.

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WindowGenerator

- **Input Width** is a parameter that determines the number of consecutive data points to use as input.
- **Label Width** determines the number of consecutive data points that will be outputted.
- **Shift** is the time difference between input and label windows.

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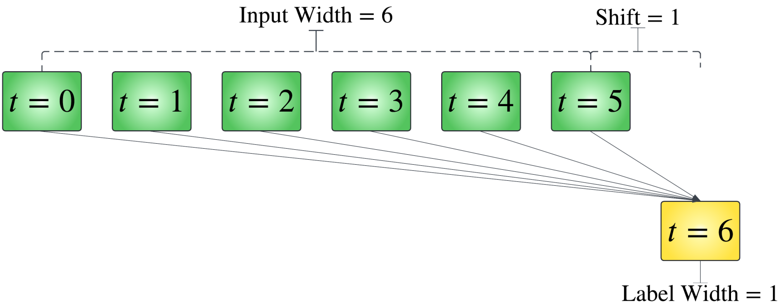

Figure 12: A sliding window illustration where the network will take the six previous input data to determine the seventh value.

- The univariate and rainfall models used this configuration.

Univariate ANNs were used as comparisons to the univariate baseline models.

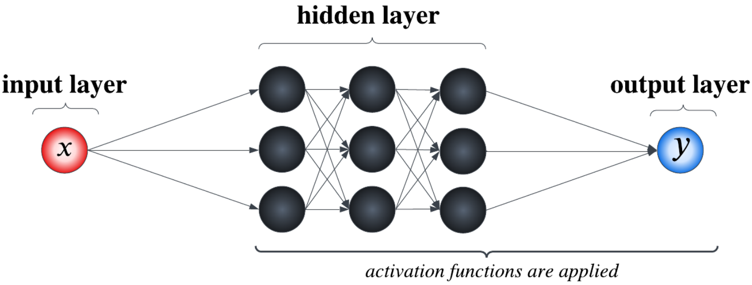

Figure 13: Univariate ANN Architecture

- In Fig. 13, x is a vector of consecutive previous water levels at the Sto. Niño Station.

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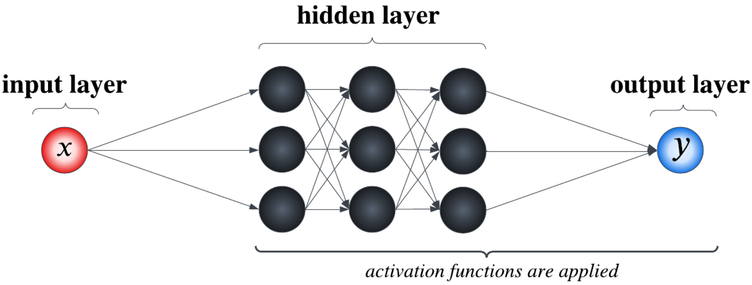

Figure 13: Univariate ANN Architecture

- The output y is the predicted water level at the same station at the current hour.

Rainfall inputs were then added to the univariate ANNs.

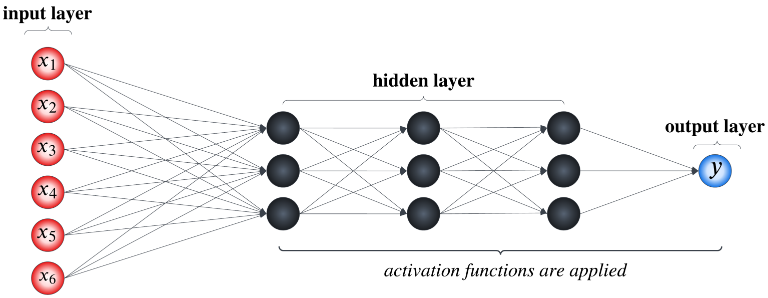

Figure 14: ANN Architecture with Rainfall Inputs

- In Fig. 14, each x_i , $i = 1, 2, ...5$ is the precipitation at the rainfall stations, and x_6 is the previous water level at Sto. Niño.

Montalban is added to increase the data points for model training.

- The best-performing ANN will incorporate the Montalban station water level data.

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- The best-performing ANN will incorporate the Montalban station water level data.
- Since Montalban is an upstream station within the MRB, its water level data can exhibit temporal patterns similar to Sto. Niño.
- This will enhance the robustness of the model's predictions and will also forecast water levels for both stations.

Snippet of the Augmented Dataset.

Table 3: First 5 columns; station is 1 for Sto. Niño, 0 for Montalban.

index	month	day	hour	Station
0	1	1	0	0
1	1	1	0	1
2	1	1	1	0

Table 4: Last 6 columns containing rainfall and water level data.

Aries	Boso	Campana	Nangka	Oro	Waterlevel
0	1	2	0	0	21.03
0	1	2	0	0	12.18
0	1	1	1	0	21.03

The study will then experiment with different lag values.

Testing the different lag values – 1, 6, and 12 – will involve two approaches:

- Adding different lag values as input features
- Modifying the window generator

Previous water level values were used as separate input features.

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- Here, only historical water level readings are used to forecast the current water level while rainfall data is limited to the most recent hour.
- This setup aims to determine whether past water levels alone are sufficient indicators of future conditions.
- However, this does not account for the delayed effects of rainfall.

The input width of the WindowGenerator was modified.

- This method ensures that for a given prediction, the model is trained using past values of both water level and rainfall data, based on the specified lag value.

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- This method ensures that for a given prediction, the model is trained using past values of both water level and rainfall data, based on the specified lag value.
- Hence, the model captures temporal patterns across multiple features, allowing it to learn both short-term fluctuations in water levels and delayed effects of rainfall on river conditions.

The same training process is followed for all neural networks.

Training Specs

- The maximum epoch was set to 20.
- Adam optimizer was used as the optimization algorithm.
- An early stopping condition was implemented.

Evaluation Metrics

MSE and NSE were used as metrics.

The performance of the models was measured using the following evaluation metrics:

- Mean Squared Error (MSE)
- Nash Sutcliffe Efficiency (NSE)

Model Explainability

SHAP values were calculated for the best-performing models.

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- The SHAP values of each feature are calculated by taking the average marginal contribution of a feature across different combinations of known and unknown features.

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Training Procedure:

1. The SHAP explainers were first trained using 50 batches from the training set.

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2. The explainer was then applied to calculate the SHAP values of the samples from the testing set.

Outline

Time series model is limited in predictive power.

AR(1)-GARCH(1,1) Model

$$\begin{cases} X_t = 0.0312 + 0.9495X_{t-1} + Y_t \\ Y_t = \sigma_t \epsilon_t \\ \sigma_t^2 = 0.0006 + 0.4580\,Y_{t-1}^2 + 0.5495\sigma_{t-1}^2 \end{cases}$$

where X_t is the current water level, X_{t-1} is the water level an hour ago, Y_t is the residual term, σ_t^2 is the volatility at time t, and $\epsilon_t \overset{iid}{\sim} \mathrm{N}(0, 1)$.

Time series model is limited in predictive power.

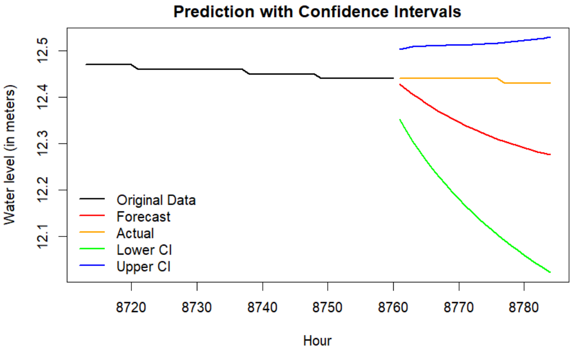

Figure 15: A 24-Hour Forecast of the Sto. Niño Water Level

- The model has an MSE value of 0.0116 and an NSE of 0.82 in a 24-hour forecast period.

Time series model is limited in predictive power.

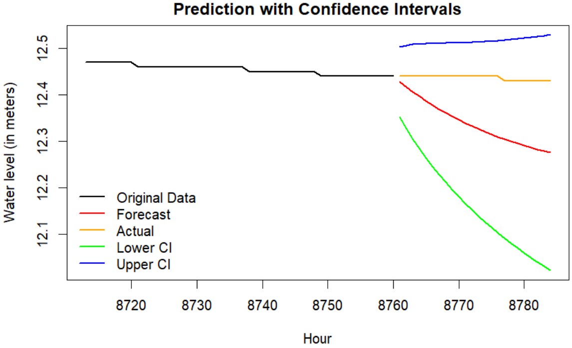

Figure 15: A 24-Hour Forecast of the Sto. Niño Water Level

- However, the final residuals show that the final model does not fully capture volatility patterns.

Univariate LSTM performs better than the AR-GARCH model.

Table 5: Performance of the Univariate ANNs on the test set

ANN Architecture	MSE	NSE
DNN	0.0462	0.8511
CNN	0.0429	0.8617
LSTM	0.0095	0.9694

- The ANNs achieve low MSE and satisfactory NSE scores.

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- The ANNs achieve low MSE and satisfactory NSE scores.
- The LSTM is the best ANN for univariate time series forecasting.

Multivariate models do not outperform the univariate ANNs.

Table 6: Performance of the ANNs with rainfall inputs on the test set

ANN Architecture	MSE	NSE
DNN	0.1068	0.6556
CNN	0.1179	0.6198
LSTM	0.0251	0.9187

- All models perform well in terms of MSE and NSE, though they are worse than the results of the univariate models.

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- All models perform well in terms of MSE and NSE, though they are worse than the results of the univariate models.
- For this instance, the LSTM model is still the best-performing model.

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ANN Architecture	MSE	NSE
DNN	0.1068	0.6556
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LSTM	0.0251	0.9187

- The LSTM model suffers the least reduction in performance.

LSTM model with lag value 1 performed the best in both stations.

Table 7: Model Performance by Adding Lags as Input Features

lag \ metric	Sto. Niño MSE	Sto. Niño NSE	Montalban MSE	Montalban NSE
1	0.0410	0.8679	0.1011	0.6674
6	0.0535	0.8278	0.1542	0.4930
12	0.0476	0.8467	0.1972	0.3515

- Using the LSTM, the lag value of the best model at predicting water level for both stations is 1.

LSTM model with lag value 1 performed the best in both stations.

Table 7: Model Performance by Adding Lags as Input Features

lag \ metric	Sto. Niño MSE	Sto. Niño NSE	Montalban MSE	Montalban NSE
1	0.0410	0.8679	0.1011	0.6674
6	0.0535	0.8278	0.1542	0.4930
12	0.0476	0.8467	0.1972	0.3515

- Using the LSTM, the lag value of the best model at predicting water level for both stations is 1.
- The NSE for lags 6 and 12 at Montalban station are not satisfactory.

LSTM model trained on 1 hour of previous data performs the best.

Table 8: Model Performance by Modifying Window Generator

metric / lag	Sto. Niño		Montalban	
	MSE	NSE	MSE	NSE
1	0.0399	0.8713	0.1276	0.5806
6	0.0502	0.8380	0.1079	0.6454
12	0.0490	0.8423	0.1095	0.6406

- Setting input width as 1 yields the best performance for predicting Sto. Niño water level.

LSTM model trained on 1 hour of previous data performs the best.

Table 8: Model Performance by Modifying Window Generator

lag \ metric	Sto. Niño MSE	Sto. Niño NSE	Montalban MSE	Montalban NSE
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6	0.0502	0.8380	0.1079	0.6454
12	0.0490	0.8423	0.1095	0.6406

- Here, the NSE for all models are satisfactory.

Models with more features has more fluctuations.

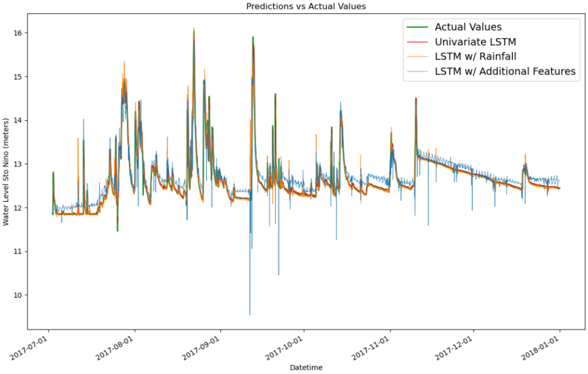


Figure 16: Predictions of different models for Sto. Niño water level.

- The model trained on the augmented dataset and input width of 1 has multiple underestimations.

Models with more features has more fluctuations.

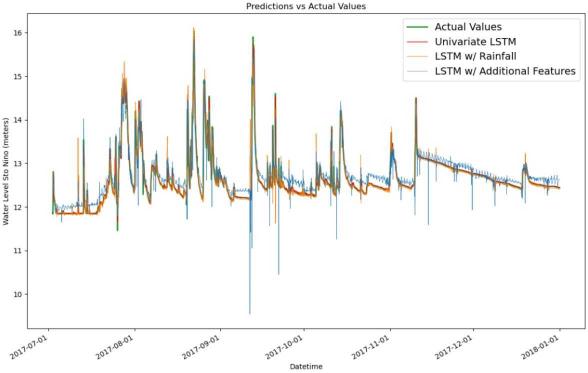


Figure 16: Predictions of different models for Sto. Niño water level.

- On the other hand, the LSTM with rainfall inputs has overestimations.

The LSTM with rainfall inputs predicts closest to the peak.

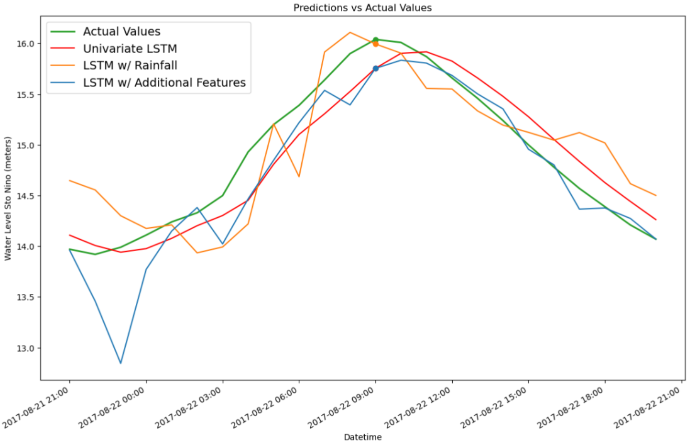


Figure 17: The model predicts a water level of 15.995 m, the closest to the peak of 16.04 m.

Both models do not predict Montalban water level well.

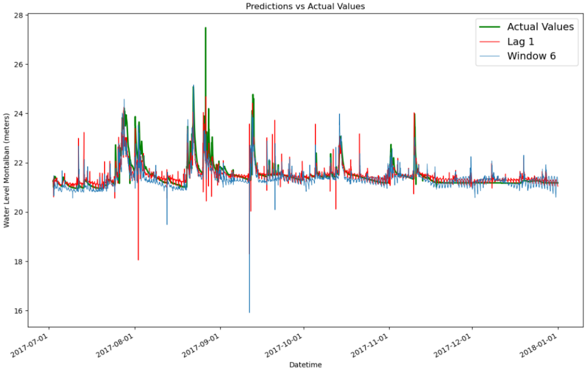


Figure 18: Predictions of different models for Montalban water level.

- Fluctuations, overestimations, and underestimations are observed across the graph.

The models underestimate the peak water level.

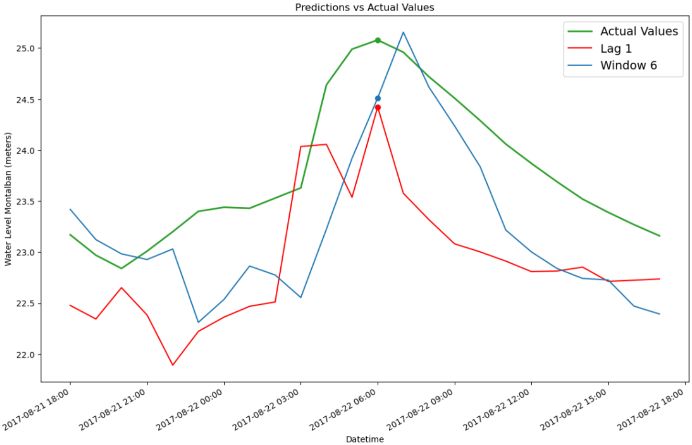


Figure 19: The model trained on windows of data exceeds (25.16 m) the peak (25.08 m) but in the following hour.

Mt. Oro has the largest contribution among rainfall stations.

Feature	Model with window (Sto. Niño)	Model, no windows (Montalban)
Waterlevel	0.4698	0.5258
day	0.0450	0.0318
month	0.0289	0.2461
hour	0.0217	0.0404
Rainfall_Oro	0.0171	0.0669
Rainfall_Aries	0.0135	0.0100
Rainfall_Boso	0.0103	0.0110
Rainfall_Nangka	0.0091	0.0116
Rainfall_Campana	0.0068	0.0126
Station	0.0000	0.0000

- The previous water level had the largest contribution to the prediction for the current water level.

High feature values induce a greater change in prediction value.

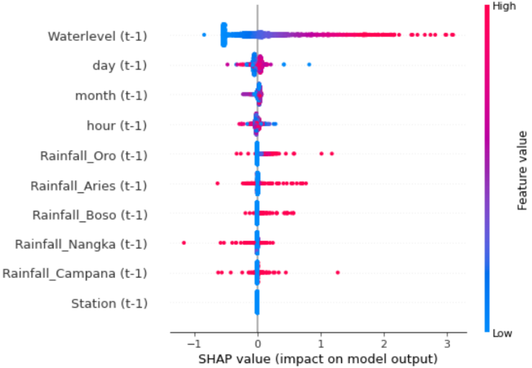


Figure 20: Summary Plot of the Individual Predictions of the Model with Window on the Sto. Niño Test Data.

High feature values induce a greater change in prediction value.

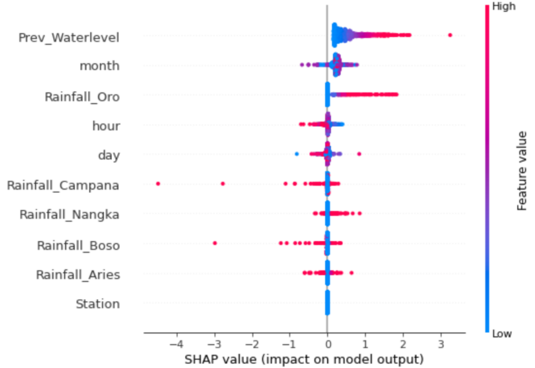


Figure 20: Summary Plot of the Individual Predictions of the Model without Window on the Montalban Test Data.

Previous water level, rainfall from Mt. Aries are the most important features for Sto. Niño.

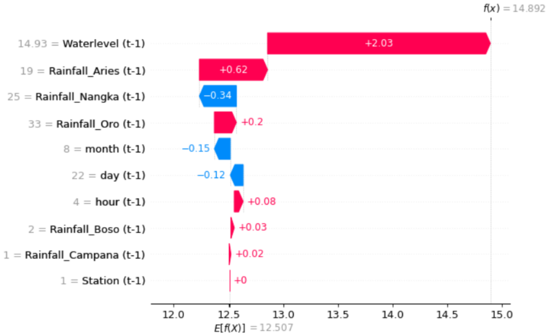


Figure 21: Waterfall Plot for a high rainfall-event on August 22, 2017 Prediction of Sto. Niño Water Level.

Previous water level, rainfall from Mt. Aries are the most important features for Sto. Niño.

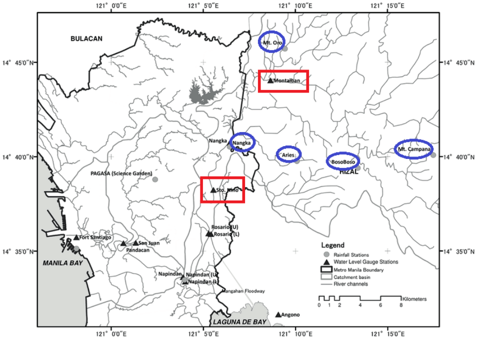


Figure 21: Marikina River Basin map; in red rectangles are the water level stations and in blue circles are the rainfall stations of interest.

Rainfall in Mt. Oro is the most important feature for the same instance on Montalban.

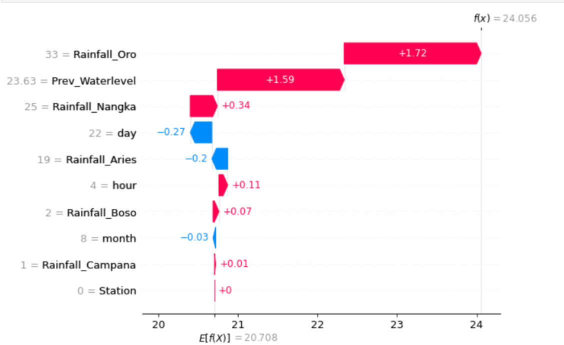
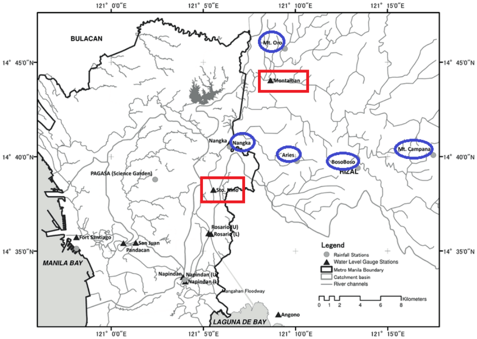


Figure 22: Waterfall Plot for a high rainfall-event on August 22, 2017 of Montalban Water Level.

Rainfall in Mt. Oro is the most important feature for the same instance on Montalban.



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Conclusion

- This study aimed to develop and evaluate predictive models for water level forecasting in the MRB using the ANNs.

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- The LSTM provided superior performance in both the univariate and multivariate settings.

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- Upon adding Montalban station data and experimenting with different lags, results revealed that using the WindowGenerator generally yielded better performance.
- SHAP analysis confirmed that the previous water level was the most influential predictor for forecasting water levels, while rainfall data from specific stations also played a role.

Conclusion

- The best-performing model in predicting the water level at Sto. Niño was the LSTM model with 6 hours of previous water level data.

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- The best-performing model in predicting the water level at Sto. Niño was the LSTM model with 6 hours of previous water level data.
- For the Montalban water level, the LSTM model using 1 hour of previous water level and the current rainfall data performed the best.

Recommendations for future work

- Instead of considering the whole dataset, significant rainfall events can be extracted.

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- Further feature selection can also be implemented.

Recommendations for future work

- Moreover, ANNs could be used to predict the water level at other gauging stations.

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- Moreover, ANNs could be used to predict the water level at other gauging stations.
- Hyperparameter tuning can still be done.
- Aside from basic ANN models, more complex neural networks can be used to forecast the water level.

Recommendations to stakeholders

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- Moreover, to detect peaks in water level, the previous six hours of water level and rainfall can be used.

Recommendations to stakeholders

- Invest in additional real-time sensors for water levels and rainfall to improve model accuracy.

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- Invest in additional real-time sensors for water levels and rainfall to improve model accuracy.
- Develop an automated public alert system to disseminate forecasts via SMS, social media, and websites.
- Use the model predictions to optimize evacuation plans, particularly in high-risk zones.