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A Comparative Analysis of Time-Series Models of ARIMA and Prophet IoT-Based Flood Forecasting in Sungai Melaka

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Abstract. Flood prediction is essential for mitigating disasters, especially in low-lying areas. This study presents an IoT-driven flood forecasting system that utilizes ARIMA and Prophet models to predict water levels in Sungai Melaka, Malaysia. Sensor data collected from an IoT-based flood observatory system was used to train and evaluate both models. Performance analysis based on RMSE and MAPE revealed that while ARIMA captures short-term trends, Prophet outperforms it with a lower MAPE of 6% and RMSE of 5, demonstrating superior accuracy and adaptability. Prophet's advantage lies in its robust seasonality handling, flexible trend adjustments, and ability to incorporate external regressors, making it more effective for real-time flood monitoring. The study also highlights Prophet's limitations in capturing abrupt water level spikes, suggesting that integrating environmental factors such as rainfall intensity and upstream discharge could enhance predictive accuracy. The findings contribute to the development of AI-driven flood warning systems, supporting urban disaster management strategies.

Keywords: Prophet, ARIMA, IoT-based Flood Forecast, Sustainable Flood Management, AI-Driven Disaster Mitigation

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1. Introduction

Flood is known as one of nature's destructive forces and happens very quickly with no prior warnings. It has the ability to demolish houses, ruin crops, wreck cars even can sweep human away. The tropical weather in Malaysia makes floods a particularly significant issue. The eastern part of Malaysia as well as Peninsular Malaysia both regularly encounter hot, humid and wet weather while the latter receives 2,540 mm of rainfall annually [1]. Due of this, Malaysia is especially susceptible to various floods such as monsoon floods, flash floods and recurrent flooding. Floods generally happen due to severe downpours thus building up a large amount of water and gradually submerge the area. Flash floods, on the other hand, happen far more quickly after a brief but heavy rainstorm.

Predicting floods in advance may have a significant impact on preventing damage and safeguarding life. In recent years, researchers have investigated several methods for flood prediction, such as SARIMA [2], NARX [3], [4] and ARIMA [5], [6] models. The proposed research examines the efficacy of two widely used forecasting models, Auto-Regressive Integrated Moving Average (ARIMA) and Prophet models, which has been widely used for forecasting in several domains [7]–[12], with a focus on the flash-flood prone areas along Sungai Melaka. This research attempts to determine which model has a higher accuracy for short-term flood predictions by examining historical water level data which will then be used in the proposed approach to enhance flood mitigation techniques and better protect people in Malaysia. The aim is for the water levels of Sungai Melaka to be forecasted at 10-minute intervals to mitigate flood-related disaster resulting from river overflow.

Figure 1 illustrates the location of Internet of Things (IoT) based Flood Observatory System (IFOS) system [5] located at the riverbank of Sungai Melaka. IFOS provides real-time flood monitoring and alerts to residents in flood-prone areas along Sungai Melaka. Accessible via mobile devices and web browsers, iFOS helps users track water level offering timely notifications to reduce property damage and losses during flash floods and rainy seasons. The data captured by the sensors are used as the input for the flood forecasting approach in this study.

Figure 1. Location of IFOS

Several work in this field of study have been proposed by various authors with mixed results. As an example, a flood prediction system using Artificial Neural Network (ANN) and Support Vector Machine (SVM) was proposed [13] utilizing historical data for accurate real-time rainfall prediction. However, the study lacks a thorough exploration of their respective computational demands, potential for overfitting and scalability in large-scale implementations. Meanwhile, comparisons were made between four machine learning algorithms namely Decision Tree , Random Forest, SVM, and ANN for flood prediction [14] where the results indicated that ANN has the best performance. The authors also indicated that the Decision Tree and SVM are susceptible to overfitting while ANN is found to be sensitive to hyperparameter tuning [15]. Another approach focusing on alert and rescue was proposed in [16] where the authors used IoT-based system for water level detection while integrating drone to detect and identify those stranded due to flood. Recent studies in [17] focused on developing a system which enables a four-hour flood prediction which was trained using historical data sets. On the other hand, the researchers in [18] mainly used historical data from 1986 to 2000 to forecast flooding at Dungun River by analyzing the accuracy of several machine learning algorithms. It can be noted in [19] that by carrying out appropriate parameter adjustments and thorough validation to find the optimal configuration can increase accuracy in predicting flood disasters based on rainfall indices. This indicates that parameter tuning is an important process in achieving optimality especially when real-time data is used for prediction and parameters may differ based on the location of the study. In addition, the study in [20] investigates whether the finer temporal resolution better captures flood wave characteristics and if regional LSTM models provide more accurate and robust flow predictions especially for rare extreme events, compared to local models. Zhou et al. [21] developed a deep learning-technique-based data-driven model for flood predictions in both temporal and spatial dimensions based on an integration of long short-term memory (LSTM) network, Bayesian optimization and transfer learning techniques using the case study in China. However, the authors acknowledged the lack of real-time data in the study as they depended on historical data from the hydrodynamic modeling. A machine learning classifier was used to simulate the flood inundation area in which adaptive neuro fuzzy inference system was applied to classify the simulated domain into flooded and non-flooded areas [22] with the idea that the classifier is able to reduce computational complexities in existing flood inundation modelling. Interestingly, a method that utilizes both visual information from images and textual metadata to recognize flood-related content in social media posts is presented in [23]. The proposed model employs a Convolutional Neural Network (CNN) to extract visual features from images and a bidirectional Long Short-Term Memory (LSTM) network to handle the semantic information from textual metadata. This technique requires very large training set as it uses social media as the main source which may vary in language, writing style and other elements.

Despite these advancements, a critical research gap remains in short-term flood forecasting using real-time data. Many existing models depend heavily on historical datasets which may not capture the rapid fluctuations seen in flash floods. Additionally, parameter tuning remains a challenge as model performance varies significantly across locations and environmental conditions. Given the urgent need for high-accuracy predictions in short timeframes, this study proposes an IoT-driven flood forecasting system leveraging ARIMA and Prophet models. By integrating real-time sensor data from Sungai Melaka, this research aims to evaluate the performance of these models, address computational efficiency and enhance predictive accuracy. The findings will contribute to the development of AI-driven flood monitoring systems capable of providing reliable early warnings and disaster mitigation strategies.

2. **Methods**

2.1 Prophet model

The Prophet model is an open-source time-series model [24] generation algorithm developed by Facebook. It excels at modelling time series with numerous seasonality and it avoids some of the limitations that SARIMAX and RNN-LSTM have which are too many stringent data requirements for SARIMAX and a significant level of knowledge about neural network architecture for RNN-LSTM. At its core, the Prophet model is an additive regression model, that is shown in Equation 1, with three-time functions, which are growth g(t), seasonality s(t), holidays h(t), and an error term ∈_t [13].

$$\boldsymbol{y(t) = g(t) + s(t) + h(t) + \in_t} \qquad (1)$$

2.2 ARIMA Model

Auto-Regressive Integrated Moving Average (ARIMA) is a class of models that explain the trend of a given time series by referring to its previous values. For example, its lags as well as the lagged prediction error. By evaluating the previous values, the equation can be applied in time series forecasting. There are 3 terms characterized in the ARIMA model, which are p, q and d. The order of the AR term is denoted by p; the number of differencing necessary to make the time series steady is denoted by d; the order of the MA term is denoted by q [25].

2.3 Root Mean Squared Error (RMSE) & Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) are applied in order to determine the accuracy of the model [14].

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{2}$$

$$\boldsymbol{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \tag{3}$$

Equation (2) and (3) show the equation for RMSE and MAPE respectively where $\hat{\boldsymbol{y}}_{\boldsymbol{i}}$ is the predicted value for the i^th^ observation, $\boldsymbol{y}_{\boldsymbol{i}}$ is the actual value for the i^th^ observation and N is the total number of observations.

2.4 Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC)

To evaluate the performance of the ARIMA algorithm, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) were used to obtain the combination of the hyperparameters that best fits the original series. AIC is widely used to measure the performance of a statistical model and it quantifies the goodness of fit to the training set [16]. The equation of AIC is stated in (4) while equation (5) indicates that of BIC where p_i refers to the number of the estimated parameters while L_i is the maximum likelihood function value of the model for both equations [16].

$$\boldsymbol{AIC} = -2\ln(L_i) + 2p_i \tag{4}$$

$$\boldsymbol{BIC} = -2\ln(L_i) + p_i \log n \tag{5}$$

2.5 Data

The IFOS is designed as a water level monitoring and flood warning system which is located at Pengkalan Rama Jetty, Sungai Melaka, coordinates 2°12'30.3"N, 102°15'02.8"E. For developing ARIMA and Prophet models, a dataset from 5:40 am May 2, 2021 to 6:10 am May 3, 2021 were used with water level measurements in centimeters recorded every 10 minutes. The pre-processed dataset comprising 148 samples was split into a training set (112 samples or about 76%) and a validation set (36 samples or about 24%) which is adequate in the events of limited data [26].

```
param_space_prophet = {
    "changepoint_prior_scale": [0.01, 0.1, 0.2, 0.3, 0.4, 0.5],
    "seasonality_prior_scale": [0.01, 0.1, 0.5, 1.0, 5.0, 10.0],
    "seasonality_mode": ['additive', 'multiplicative'],
    "seasonality_setting": ['auto', 'true', 'false']
}
```

(a)

```
param_space_non_seasonal = {
    "p": [0, 1, 2],
    "d": [1],
    "q": [0, 1, 2],
    "with_intercept": ["auto"],
    "seasonal": [False]
}
```

(b)

```
param_space_seasonal = {
    "p": [0, 1, 2],
    "d": [1],
    "q": [0, 1, 2],
    "P": [0, 1],
    "D": [1],
    "Q": [1, 2],
    "s": [7],  # Weekly periodicity
    "with_intercept": [False],
    "seasonal": [True]
}
```

(c)

Figure 2. Hyperparameter Tuning via Bayesian Optimization

2.6 Hyperparameter Tuning Using Bayesian Search Optimization

This study implements a Bayesian optimization approach to systematically tune the hyperparameters of ARIMA and Prophet models for flood forecasting. Bayesian optimization is a probabilistic model-based approach that efficiently searches the hyperparameter space by balancing exploration and exploitation. This method significantly reduces the computational burden associated with exhaustive grid search and traditional trial-and-error methods ensuring optimal parameter selection within a feasible time frame.

The Prophet model has a set of input parameters that can affect and influence the performance of the model in forecasting. Optimizing the forecasting accuracy of the Prophet model depends on hyperparameter adjustment. The changepoint prior scale lets the model adapt to data changes without being misled by noise by varying its sensitivity to trend fluctuations. Not less important are the seasonality prior scale and seasonality mode, which enable the model to faithfully depict seasonal trends. How well the model captures data subtleties depends much on the choice between additive or multiplicative seasonality.

Meanwhile, The success of the ARIMA model is closely linked to its parameters including p (the autoregressive term), d (the differencing term), q (the moving average term), m (the seasonal differencing term) and the consideration of seasonality. When making predictions, the accuracy of the forecasts can be greatly influenced by selecting the appropriate combination of these parameters. This is where hyperparameter tweaking becomes crucial. It is evident that the process of determining optimal parameters is computational expensive as well as necessitates a careful equilibrium between the complex nature of the model and its ability to accurately represent the data in order to prevent overfitting or underfitting.

3. Results & Discussion

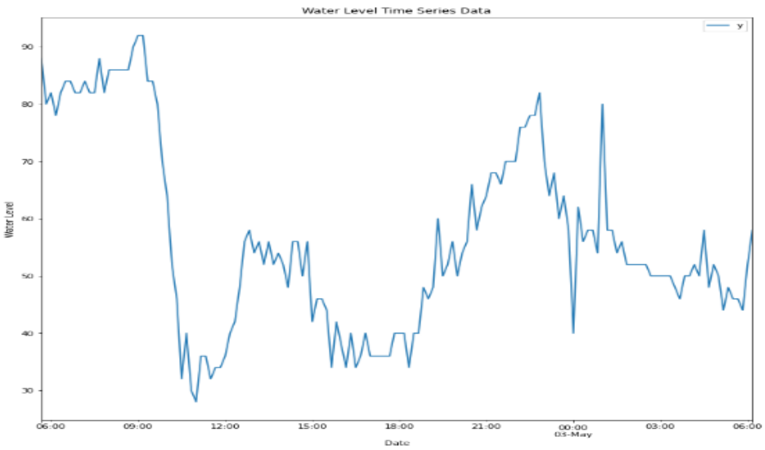


Figure 3. Water Level Time Series Data from IFOS.

Figure 3 shows the water level time series over a 24-hour period therefore highlighting notable changes in water levels over a rather brief time frame. These fluctuations draw attention to the dynamic character of the water levels in the under observation area most likely driven by different environmental elements including rainfall, tidal fluctuations or upstream water flow. Therefore, this shows that developing a flood warning system that is able to make quick judgments to minimize flood effects in flood prone areas is extremely important and beneficial. Another key aspect illustrated by Figure 3 is that water level data and the parameters involved in the decision-making varies according to the location hence the importance of hyperparameter tuning approach used in this study [27].

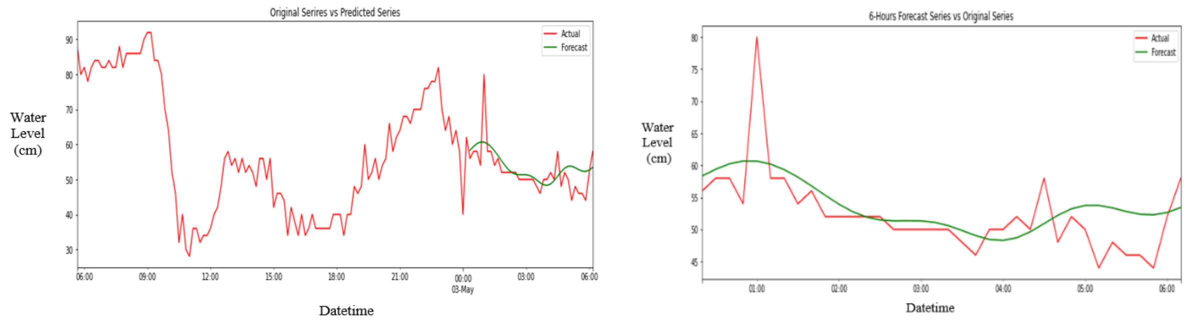
3.1 Hyperparameter Tuning Outcome for Prophet

To analyze the performance of each Prophet model, a diagnostic test was conducted using different parameter combinations. The test compared forecasts to actual water levels from the validation set using MAPE and RMSE as key metrics that helped to identify the Prophet model that produces best performance for each parameter set.

Table 2. Hyperparameter combinations for Prophet

Model	Param 1	Param 2	Param 3	Param 4	MAPE (%)	RMSE
0	0.5	10.0	Additive	Auto	46.55	24.88
1	0.01	0.01	Multiplicative	False	24.28	14.09
2	0.01	5.0	Additive	True	10.65	7.62
3	0.1	0.01	Additive	Customized	6.41	4.98

Table 2 provides the optimal combinations for four hyperparameters: Param1 (Changepoint_prior_scale), Param2 (Seasonality_prior_scale), Param3 (Seasonality_mode) and Param4 (Seasonality settings). The model with the lowest MAPE of 6.41% and RMSE of 4.98 was determined to be the best-fitting Prophet model. This model used Changepoint_prior_scale set to 0.1, Seasonality_prior_scale at 0.01, an additive seasonality mode and customized seasonality settings. These optimal settings show the model's ability to capture data trends and seasonal patterns accurately ensuring precise forecasting. The forecast was produced from 00:00 03-05-2021 to 06:00 on the same day and the results are shown in Figure 4.2. The diagram illustrates the actual water levels indicated by the red line and the forecast values indicated by the green line allowing for a direct evaluation of the model's accuracy. Upon additional analysis, it becomes evident that there is a sharp surge in the recorded water levels early in the time frame peaking at around 80 cm around 00:30. The forecast did not accurately capture this sudden increase as the expected values shown by the green line remained consistent and did not account for the rapid peak. This disparity may indicate that the Prophet model has insufficient capacity to handle sudden, irregular surges. Prophet is specifically designed to catch general patterns and seasonal variations rather than focusing on unusual and extreme data points. This is why the projected series seems to be smooth even during periods of sharp rise.



(a) (b)

Figure 4 (a) and (b). Observed and Forecasted Water Levels using Prophet Model.

After the spike, from approximately 01:00 to 02:30, the observed water levels show a steady decrease with fluctuations around the 55-50 cm mark. During this period, the model's forecast closely follows the general trend of the actual data. The green forecast line captures the declining trend though it is slightly smoother than the actual series which has more variability. This smoothing effect is a characteristic of the Prophet model which tends to average out short-term fluctuations focusing more on the overall trend rather than on day-to-day or hour-to-hour volatility. In this case, the model provides a good approximation of the water levels accurately predicting the gradual decline after the peak. In the period of 02:30 and 04:30, the water levels vary around 50 cm but the forecast model shows a modest, smooth upward curve. There is some variation in both the predicted and actual data with the model underestimating small spikes and overestimating little valleys.

Nevertheless, the variation is insignificant and is unlikely to influence the forecast's reliability. During the later part of the forecast period, specifically between 05:00 and 06:10, there is a simultaneous rise in both the observed and predicted water levels. Nevertheless, the observed series exhibits a more significant growth compared to the forecast, with a sudden surge towards the end of the specified period. The forecast does catch this upward tendency but with a tiny delay in matching the magnitude of the actual increase. This implies that although the model is capable of forecasting the overall trajectory of future trends, it may have difficulties in accurately capturing the complete magnitude of abrupt and significant rises in water levels.

3.2 Hyperparameter Tuning Outcome for ARIMA

Table 3. The combinations of the hyper-parameters for non-seasonal ARIMA based on AIC and BIC

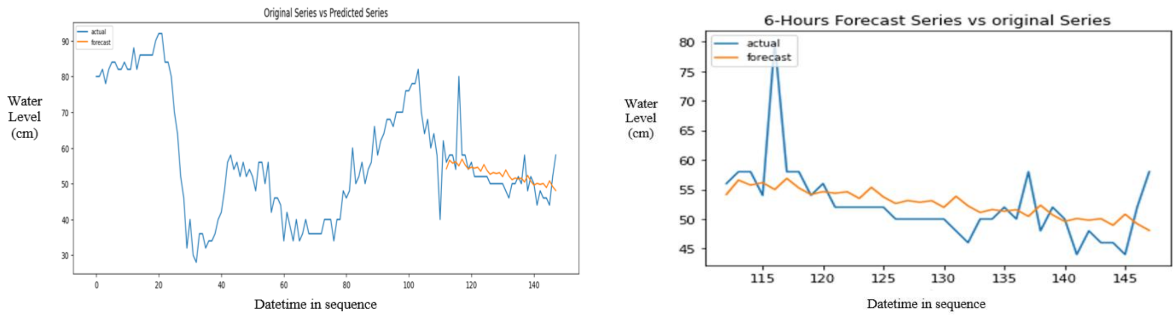
No	p	d	q	m	with_intercept	Seasonal	AIC	BIC
1	1	1	0	1	False	False	930.79	936.77
2	2	1	1	1	False	False	931.35	943.31
3	1	1	0	1	True	False	932.57	941.54
4	2	1	0	1	False	False	932.79	941.76
5	1	1	1	1	False	False	932.79	941.76
6	2	1	1	1	True	False	933.28	948.23
7	2	1	0	1	True	False	934.57	946.53
8	1	1	1	1	True	False	934.57	946.53
9	0	1	1	1	False	False	934.93	940.91
10	0	1	1	1	True	False	936.69	945.66

The analysis as shown in Table 3 revealed that the model with p=1, d=1 and q=0 exhibited superior performance as evidenced by the lowest AIC and BIC values. This suggests that this particular combination achieves an optimal trade-off between model complexity and data fit. Besides, the combinations of the hyper-parameters were re-tested using Auto ARIMA by setting the seasonal to become 'True' and m to become '7'. By doing this, the model will correspond to the recurrent periodicity of daily. To perform ARIMA with seasonal order, P, D, Q and s are the seasonal components needed (which is equal to m). P and Q denote the AR and MA orders, D indicates the integration order, as well as s in the integer that represents the periodicity of the model. For the evaluation of the seasonal ARIMA model, only AIC was used as the performance metric. Table 4 shows the combinations of the hyper-parameters for each set of p, d, and q parameters with seasonal. The combinations were sorted in ascending order based on the AIC values. As the combination of p=1, d=1, q=0, P=0, D=1, Q=1 and s=7 has the lowest value of AIC, therefore, the set of parameters was chosen for further evaluation. The ARIMA model with an order of (1,1,0) with no seasonal component achieved a MAPE of 6.776% and when seasonality was introduced with a seasonal order of (0,1,1,7), the MAPE improved slightly to 6.541% showing marginally better accuracy in percentage error reduction.

This model was applied to generate a 6-hour lead forecast and the results are compared with the actual water level observations over the same time period as illustrated in Figure 5. The model's forecasted values (orange line) generally follow the trend of the actual series (blue line) though the model struggles with capturing sharp peaks and dips such as the significant spike around the 115th time step. The visualized results highlight some degree of underfitting especially during periods of rapid fluctuation in the water level. While the seasonal ARIMA model performs well in capturing the overall trend, its inability to predict sudden changes accurately suggests that the model is smoothing out volatile behavior potentially due to the seasonal component's influence.

Table 4. The combinations of the hyperparameters for seasonal ARIMA based on AIC

No	p	d	q	P	D	Q	m/s	with_intercept	Seasonal	AIC
1	1	1	0	0	1	1	7	False	True	915.160
2	2	1	1	0	1	1	7	False	True	915.428
3	1	1	0	0	1	2	7	False	True	917.132
4	1	1	0	1	1	1	7	False	True	917.133
5	2	1	0	0	1	1	7	False	True	917.149
6	1	1	1	0	1	1	7	False	True	917.155
7	0	1	1	0	1	1	7	False	True	919.105
8	1	1	1	0	1	2	7	False	True	919.124
9	1	1	1	1	1	1	7	False	True	919.126
10	0	1	1	0	1	2	7	False	True	921.067



(a) **(b)**

Figure 5 (a) and (b). Observed and Forecasted Water Levels using ARIMA Model.

This consistent lag in predicting extreme variations implies that while the model is effective for broader trend forecasting, it may require additional adjustments or complementary models to improve short-term predictive accuracy for extreme events. On the other hand, the Prophet model shows superior performance in short-term predictions especially in the capture of the finer details of abrupt changes as indicated by its lower MAPE and RMSE values. Compared to the ARIMA model which may require extensive parameter tuning to be able to adapt to such changes, the Prophet model's adaptability allows it to autonomously manage seasonality and trend shifts.In addition, Prophet's additive and multiplicative seasonality offers a more robust framework for time series with irregular cycles or abrupt level shifts such as the water levels observed in this study. Consequently, Prophet's ability to adapt to these general fluctuations results in better forecasts rendering it a more suitable option for predicting the behavior of the water levels in this instance. Therefore, Prophet model will be applied in the following section to study its performance for 7-days forecast in the following sub-section.

3.3 7-Days Prediction using Prophet Model

The Prophet model's ability to predict future water levels is analyzed using a 37-day dataset. The model was constructed using 1-hour interval of water levels from September 26, 2021, to November 1, 2021. Using the patterns observed in the training set, the model is tasked with generating a 7-day forecast for the validation period. The model's precision is contingent upon its capacity to identify both abrupt fluctuations and incremental trends, as water level data is exceedingly dynamic.

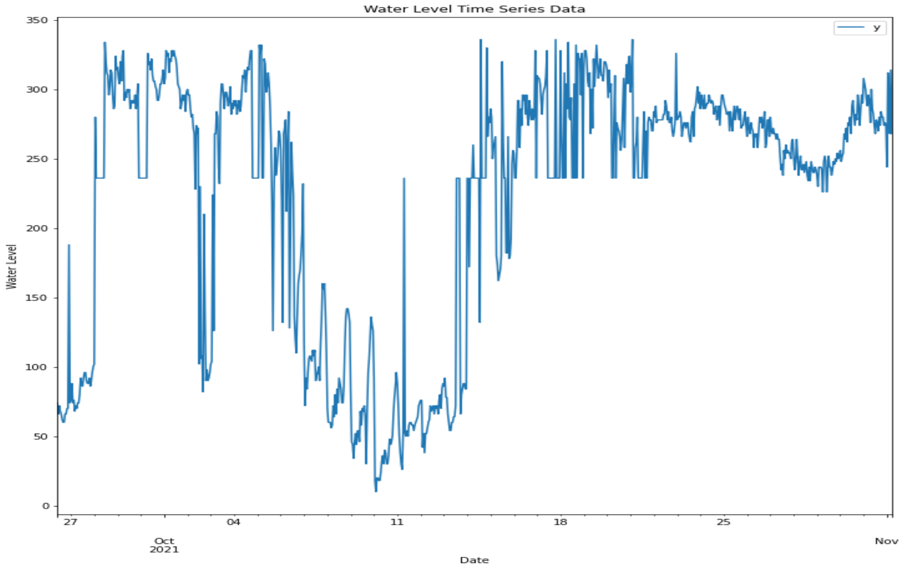


Figure 6. Water-level time-series data for 37 days.

Table 5. Parameters involved in Bayesian Optimization for Prophet model for 7-days prediction

Parameters	Description	Options
Changepoint_prior_scale	Identify the trend's flexibility, and specify the trend changes at changepoints	0.001,0.01,0.025,0.05,0.075,0.1,0.2,0.3,0.4,0.5
Seasonality_prior_scale	Govern the seasonality's adaptability.	0.001,0.01,0.025,0.05,0.075,0.1,0.2,0.3,0.4,0.5
Seasonality_mode	Tuned based on the trend of the time series input data.	Additive/ Multiplicative
Seasonality_setting • Yearly_seasonality • Weekly_seasonality • Daily_seasonality	Depend on if the date frame of the time series input data.	True/ False

The parameters that were applied for optimization are shown in Table 5. The analysis of three Prophet model configurations shows that Prophet model with a changepoint_prior_scale of 0.01, seasonality_prior_scale of 0.3, additive seasonality mode and no seasonal adjustments performed best achieving a MAPE of 6.17% and RMSE of 18.92. The Prophet model's water level forecast indicated by the green line does not reflect the large changes in the real data which is represented by the red line. The model seems to be prioritizing long-term patterns and seasonality above short-term volatility based on Figure 6. The predicted line remains unchanged which actually indicating that the model underfits the data [28]. Prophet's reliance on smooth, continuous assumptions hinders accurate flood predictions due to abrupt, unforeseen fluctuations. The model's changepoint and seasonality parameters are rigid thus limiting its ability to respond to unexpected data changes [28]. These two are known limitations of Prophet model thus adding additional regressors like meteorological data can boost Prophet's flood predictions by capturing abrupt water level fluctuations. In flood-prone areas, rainfall intensity, upstream water releases, temperature, and wind speed can immediately affect river levels. By adding these variables to the model, the Prophet algorithm may better predict water level variations. This would improve the model's ability to forecast sudden decreases or spikes which is now lacking when using only past water level data.

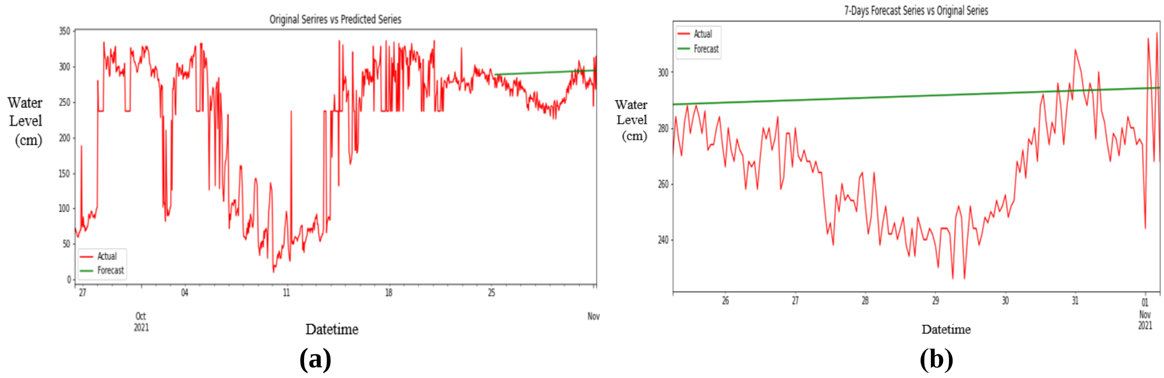


Figure 6 (a) and (b). Observed and Forecasted Water Levels using ARIMA Model.

4. Conclusion

When 6-hour data on water levels were used to compare the Prophet and ARIMA models for flood forecasting, it was clear that both were able of making short-term predictions at an acceptable level. Prophet, which is known for being able to adapt to trends and seasonal changes had lower MAPE and RMSE error rates than ARIMA. This made it a better choice for tracking floods in real time. ARIMA, on the other hand, needed a lot of parameter changes to deal with seasonality but it had trouble with fast changes which caused it to underfit during instances of sharp water level changes. Because of this, Prophet was picked and performed at producing a 7-day forecast. However, the model did not do very well especially when it came to predicting sudden changes in water levels. Perhaps this was because Prophet focused on longer-term, smoother trends and patterns. Adding outside factors like temperature and rainfall could help Prophet react better to sudden changes and make it more accurate. Also, looking into other models like SARIMA or ARIMAX, which are better at dealing with seasonality and outside factors or using deep learning methods like LSTM to pick up on complex patterns could help with better flood forecasting especially when short-term changes need to be taken into account.

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