ResearchProject

tapiwamwila

February 2024

Streamflow Analysis

The dataset under analysis comprises hourly streamflow data, encompassing measurements of discharge, stream temperature, and stream electrical conductivity, commencing from the onset of the year 2021. These variables exhibit interdependence: stream temperature influences discharge via mechanisms such as thermal expansion, snow/ice melting, and evaporation, with elevated temperatures generally augmenting discharge. Similarly, stream electrical conductivity reflects factors like dissolved solids concentration, groundwater interaction, and pollution, which can, in turn, impact discharge rates by influencing water density, groundwater inflow, and stream morphology. Noteworthy minimum values include a discharge of 2.07 L/s and a stream electrical conductivity of 0.069 ms/cm.

Examining stream temperature reveals distinct trends: an initial period of low temperatures extending to the second month, followed by a gradual increase until June. Subsequently, there's a more pronounced rise, denoting hot summers, with a subsequent decline to 15 degrees Celsius. A general smooth decrease from July to October is observed, potentially indicative of gaps in recording, followed by a modest decline through December, with recorded temperatures as low as 0.2 degrees Celsius. Regarding stream electrical conductivity, the highest recorded value is approximately 0.35 ms/cm in July, possibly attributed to the summer season. From March to June, an increase in electrical charge is evident.

Employing lagging as a time-series technique aids in predicting daily discharge. Initially lagged by six intervals, subsequent iterations increased to fifteen lags, alongside linear regression. Higher lag numbers correspond to greater deviations between predicted and actual discharge. Notably, a reduction in the number of variables results in closer fitting, approaching near-perfect alignment between actual and predicted values. From the plot, we notice that the actual values and the prediction are further apart from each other. From the plot, we notice the actual and predicted values are very close to each other.

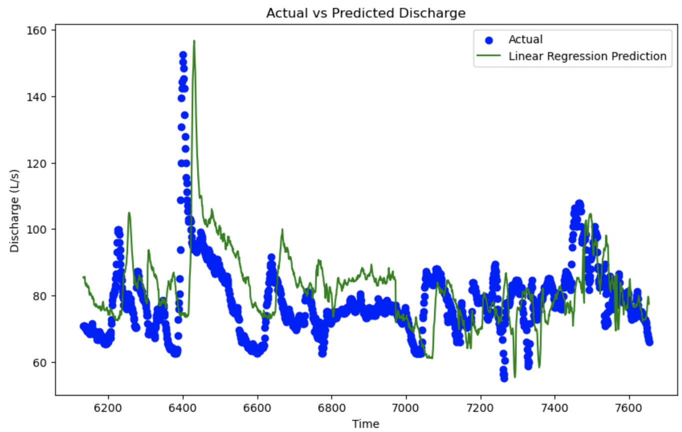

Figure 1: Plot for a larger lag number

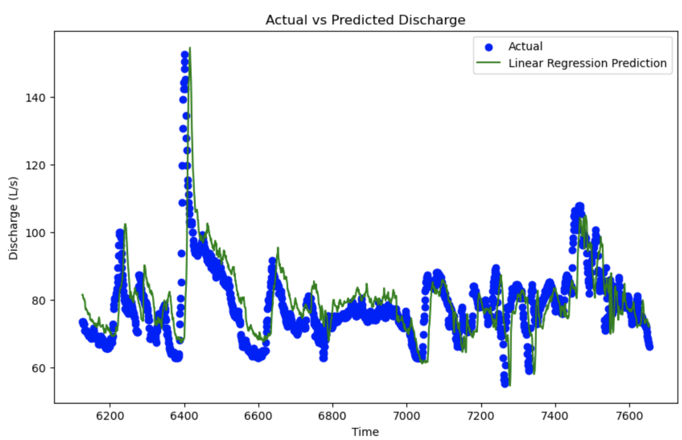

Figure 2: Plot for a smaller lag number

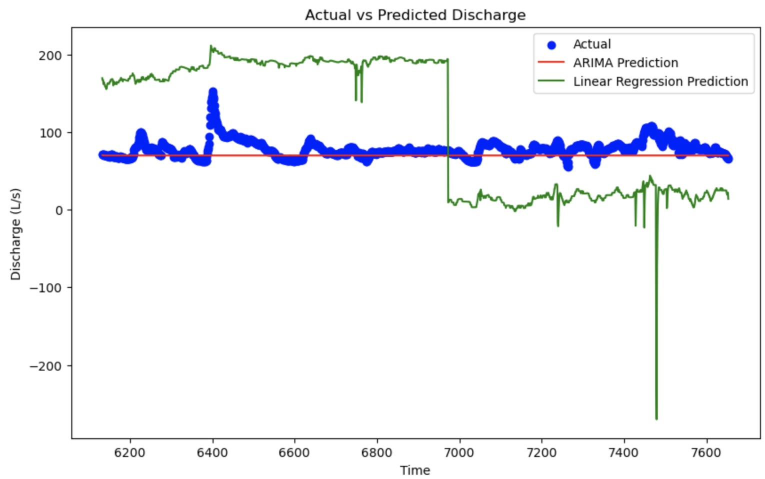

Figure 3: A comparison of models

Timeseries

Exploring time-series methodologies further, we investigated alternative models beyond lagging, specifically focusing on ARIMA (AutoRegressive Integrated Moving Average). Comparing model performances, ARIMA emerges as superior to linear regression in predicting streamflow, evidenced by closer alignment between ARIMA predictions and actual data.