EVALUATION OF RIVERINE WATER TEMPERATURE IN A-CLASS RIVERS IN ARIAKE BAY BASIN BY ARTIFICIAL INTELLIGENCE

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Introduction

In recent years, there have been many phenomena in which environmental anomalies due to climate change are suspected. With the progress of global warming, also there is a concern about the rise in riverine water temperature in addition to air temperature (Shiroiwa *et al.*, 2006; Miyamoto *et al.*, 2010). It is expected that rising riverine water temperature may affect seawater temperature in a region of freshwater influence (ROFI), but few studies have focused on this. In this study, we focused on evaluating the effects of other significant factors than air temperature on riverine water temperature. We attempted to develop a noble riverine water temperature evaluation model using the artificial intelligence (AI) technique.

Methodology

The target rivers in the present study are the seven class A rivers flowing into the Ariake Sea. (*see* Fig.1).

Analysis was performed using hourly data of air temperature, river flow discharge, precipitation, and global radiation as learning data.

Using the neural network (NNW) function (*neuralnet* in the neuralnet package) of the statistical analysis software R (Ver.3.5.1), the riverine water temperature was used as the target variable, and the air temperature, river flow discharge, and global solar radiation were explanatory variables. The training data was the data for one year of 2016.

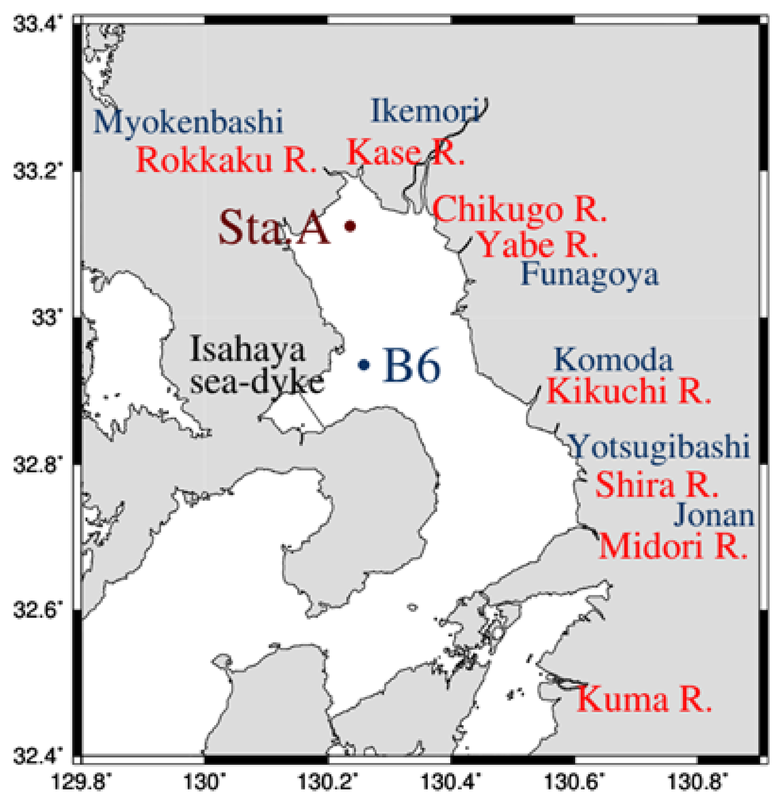

Figure 1. Target rivers and water temperature measurement stations

Conclusions

✓Some explanatory variables were added to suppress diurnal variation. The daily fluctuation has decreased, but the prediction accuracy is poor.

✓In future studies, we must continue to adjust the explanatory variables and use other types of NNWs that are better suited for time series data to improve accuracy.

References:

Shiroiwa, J., *et al.*(2006). Influence of water temperature of river by climate change, *J. of JSCE*, 50.

Miyamoto, H., *et al.*(2010). An impact analysis of climate change on stream temperatures in a river basin, *Ann. J. of Hyd. Eng.*, JSCE, 54.

Results and Discussion

Figures 2 to 4 show the time series of predicted values and measured values (learning data) in May, 2016 in case that the NNW model trained only for 11 months excluding a month of May.

✓**Figure 2**

The daily fluctuation is very large (correlation factor R=0.538, root mean square error (RMSE) value: 2.837).

✓**Figure 3**

It shows the case that temporal and spatial elements are added. The learning data were expanded not only in the downstream area but also in the upstream area and the middle. The daily fluctuation became to be smaller (R=0.759 and RMSE: 4.170). However, larger difference of the daily averaged value can be seen.

✓**Figure 4**

It shows the case adding the time information as a variable. The daily fluctuation was smaller by adding the time, but R=0.524 and the RMSE was 5.746.

✓ In both of modifications, the daily fluctuation decreased, but the error increased, and the reproducibility decreased.

✓From these results, we can understand weather condition at the lower area and river discharge are significant factors for daily averaged river water temperature at the lowest reach, but daily variation cannot be produced from only these factors.

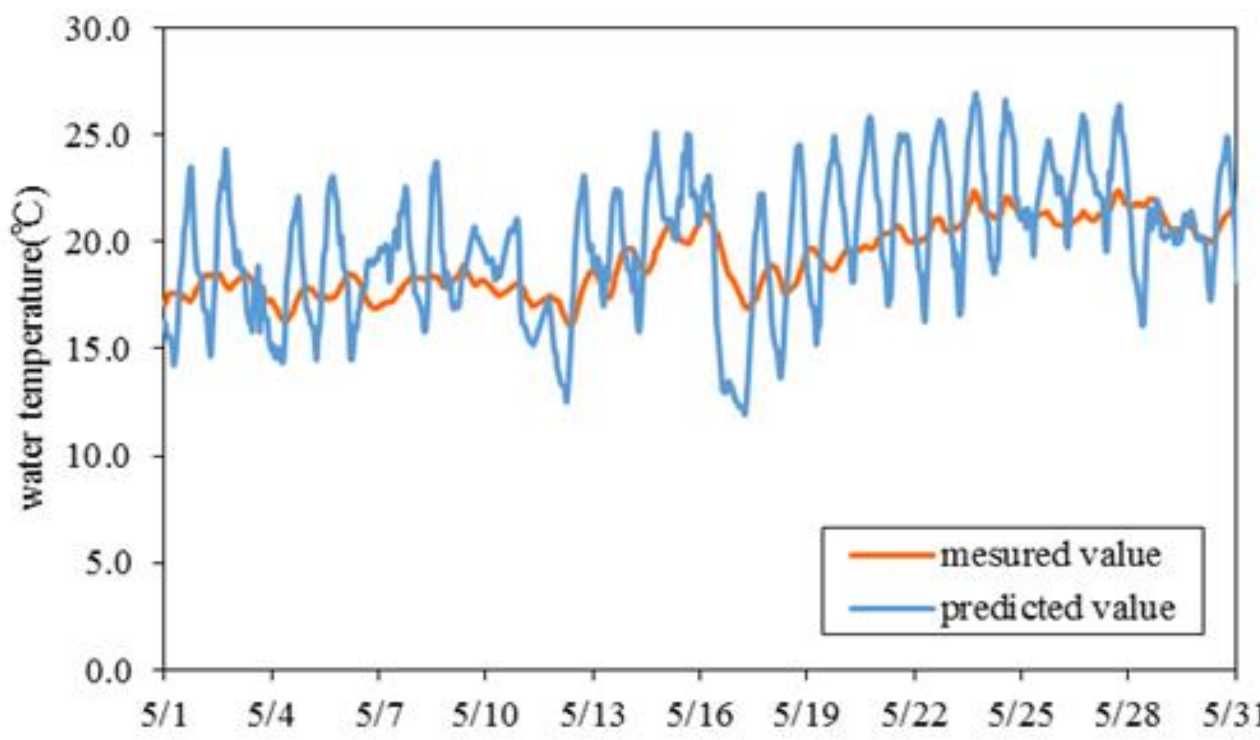

Figure 2. Time series of predicted and measured values in May, 2016. (Variables: Temperature, precipitation, river flow, global solar radiation)

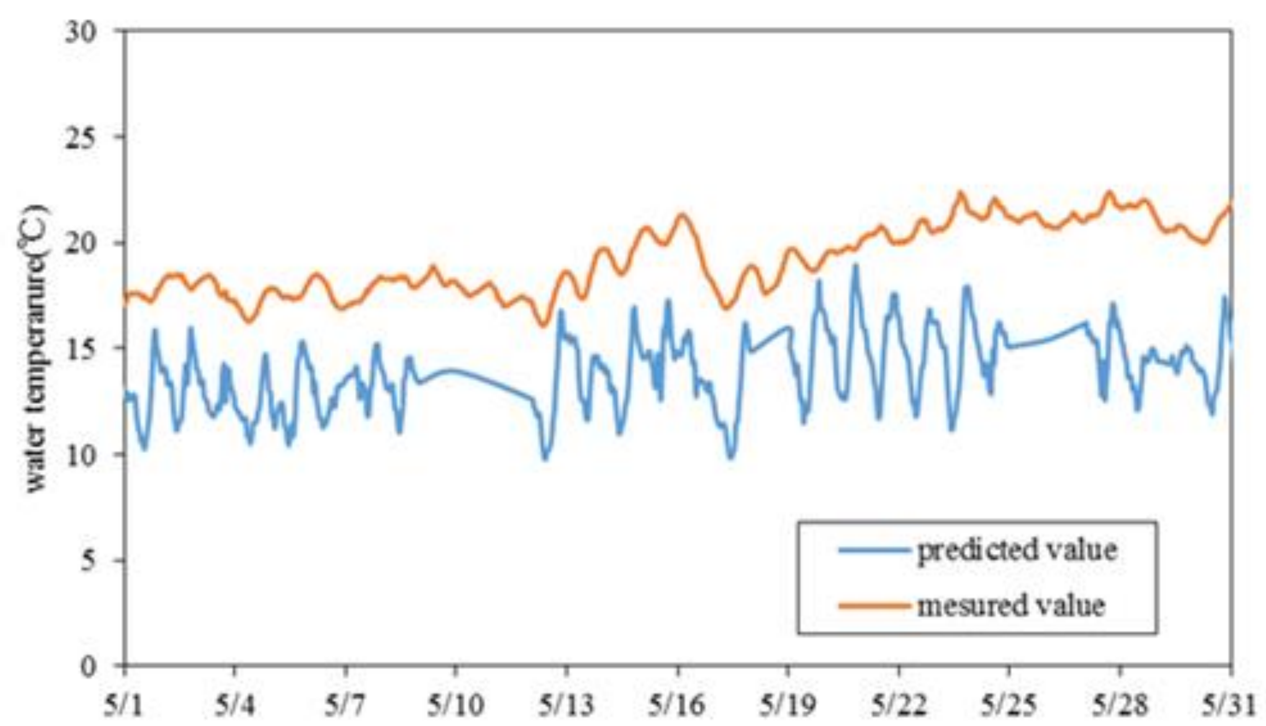

Figure 3. Time series of measured and predicted values in May, 2016. (Including variables for upstream, middle and downstream areas)

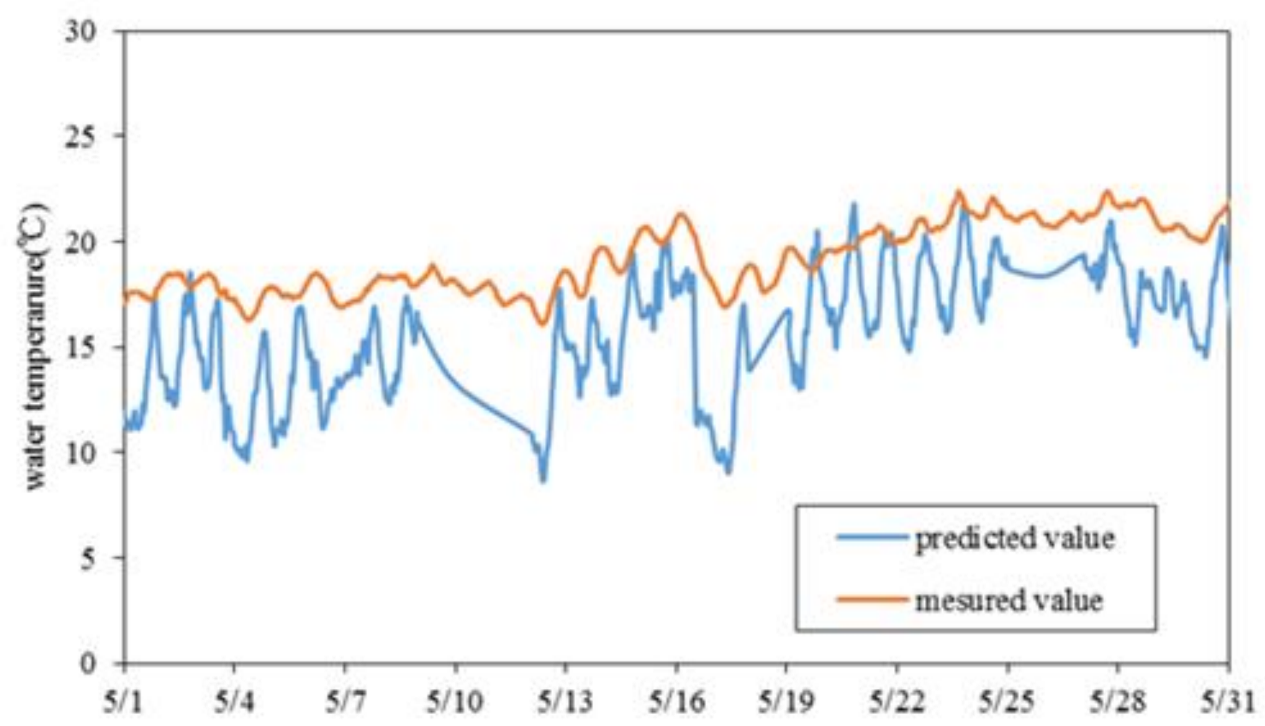

Figure 4. Time series of measured and predicted values in May, 2016. (the time was added as a variable)