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

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ABSTRACT

In recent years, we can see a lot of influences on natural environments due to climate change. For example, it has been confirmed that water temperature increases in many public waters in Japan. In this study, we focus on an influence of climate change on riverine water temperature. Tadokoro *et al*. (2018) has already developed an evaluation way using a single correlation between air temperature and riverine water temperature. But, because riverine water temperature can be determined not only air temperature, but also river discharge, precipitation, solar radiation, and so on, we need to take other effects into accounts. Thus, we try to develop a new evaluation way by using the artificial intelligence (AI) technique. We adapt the neural network (NNW) method for this modeling as an AI technique. In the new evaluation, we use four variables as explanatory variables: air temperature, one hour accumulative precipitation, and amount of global solar radiation, which are measured by Japan Weather Agency (JMA) at AMeDAS stations, and riverine discharge, which is measured by MLIT. Also, riverine water temperature in each rivers was measured by the small data-logging type thermometer in our continuous measurement for more than one year. A model for estimating river water temperature from meteorological condition data was developed using an artificial neural network. The reproducibility of daily mean value by the optimized model was high, however the daily variation had a room for improvement.

Keywords: riverine water temperature, artificial intelligence, neural network, Ariake Bay, climate change

1. INTRODUCTION

In recent years, there have been many phenomena in which environmental anomalies due to climate change are suspected. For example, water temperature has been increasing in many public water bodies in Japan (Ministry of the Environment, 2013). The IPCC 5th Assessment Report (IPCC, 2015) reported that the average air temperature and seawater temperature in oceans were rising. 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 the region of freshwater influence (ROFI), but few studies have focused on this.

Tadokoro *et al*. (2018) investigated an effect of riverine water temperature on stratification and structure of dissolved oxygen (DO) in the Ariake Sea, that is one of representative semi-enclosed bay in Japan. They quantitatively estimated an influence on stratification and anoxic water in a bottom layer under the projection of future climate change which had air temperature increase of 2 °C or 4 °C. However, they used a simple evaluation of riverine water temperature using a single correlation between temperature of air and riverine water. It is easy to speculate that only air temperature cannot affect riverine water temperature. For example, various meteorological and hydrological factors, such as river flow discharge, rainfall in a watershed area, global solar radiation, groundwater inflow, and artificial water intake, can have complex effects on river temperatures.

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 instead of physical model such as Miyamoto *et al*. (2010).

2. METHODOLOGY

2.1 Target rivers

The target rivers in the present study are the seven class A rivers flowing into the Ariake Sea, that is, the Chikugo River, the Rokkaku River, the Kase River, the Yabe River, the Kikuchi River, the Shira River, and the Midori River (see Fig.1).

In order to obtain long-term continuous temperature data of riverine water flow into the bay for rivers except for the Chikugo River in which the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) measures it, a small memory-type water thermometer (Hobo Water Temp Pro, Onset Co., Ltd.) was installed at the lowest river discharge gauge station of MLIT upper than tidal river area (see Fig.1) for more than one year from the middle of 2015 to the end of 2016. The measurement data was logged every hour. However, at the beginning of the observation (August, 2015), only the observation point Tamana in the Kikuchi River was set inside of the tidal river area. Thus, since December, 2015, it was changed to the upstream Komoda station.

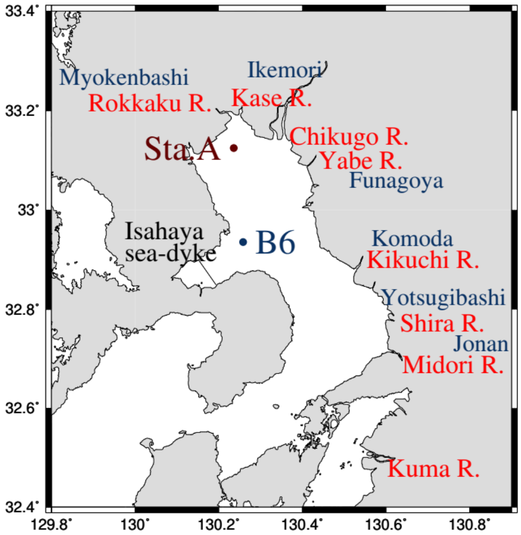

Figure 1. Target rivers and water temperature measurement stations

Analysis was performed using hourly data of air temperature, river flow discharge, precipitation, and global radiation as learning data. The air temperature and precipitation were selected from the nearest Japan Weather Agency (JMA) AMeDAS observation station from the riverine water temperature observation point. On the other hand, the global solar radiation was selected from the AMeDAS observation points where it was measured closest to the water temperature measurement point, because it was normally measured at a few stations in a given prefecture. Data of hourly river flow discharge was obtained from the MLIT. Table 1 summarizes the observatories using the data for the Chikugo River as an example.

Table 1. Weather and discharge stations for AI model in the Chikugo River

<table>
<tr><th></th><th>Air temperature,
Hourly precipitation, Solar radiation</th><th>River flow discharge</th></tr>
<tr><td>Upstream area</td><td>Hita</td><td></td></tr>
<tr><td>Middle area of the stream</td><td colspan="2">Kurume</td></tr>
<tr><td>Downstream area</td><td>Saga</td><td></td></tr>
</table>

2.2 Analysis method

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.

In this research, anthropogenic effects, such as, agricultural water usage, dam operation, and so on, are not took into account in the NNW, because it was clarified that single correlation between air and riverine water temperatures was very high in the previous research by Tadokoro *et al*. (2018).

3. 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. In this paper, results are shown only for the Chikugo River case. Although evaluations using different combinations of explanatory variables have been also performed, the results are shown in these figures for a single case that air temperature, river flow discharge, precipitation, and global solar radiation are used.

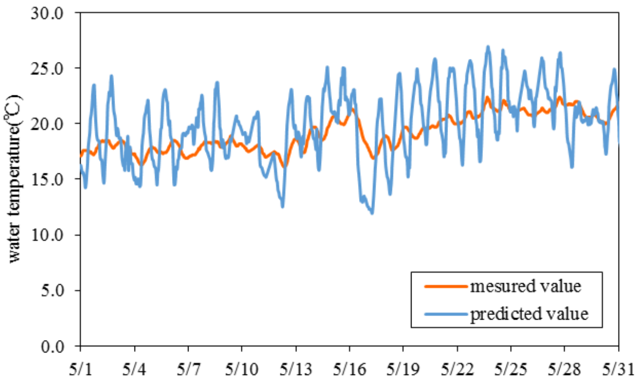

Figure 2. Time series of predicted and measured values in May, 2016.
(Variables: Temperature, precipitation, river flow, global solar radiation)

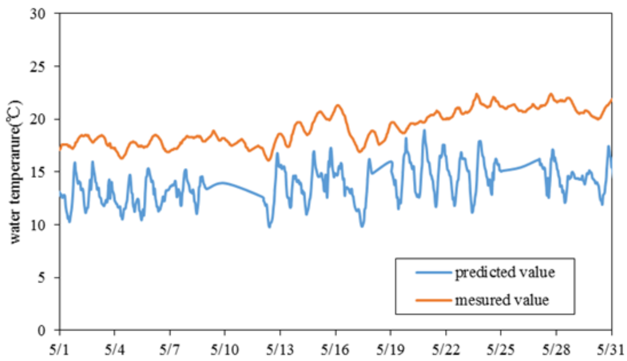

Figure 3. Time series of measured and predicted values in May, 2016
(Including variables for upstream, middle and downstream areas)

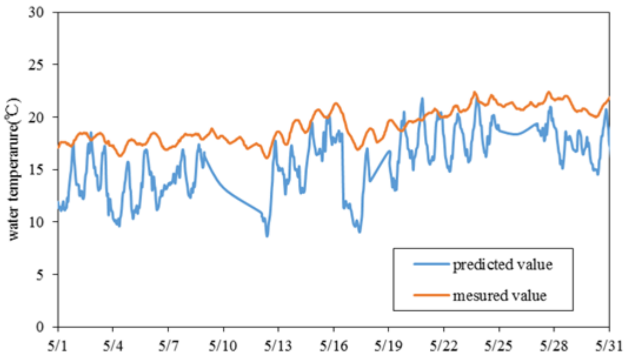

Figure 4. Time series of mesured and predicted values in May, 2016
(the time was added as a variable)

Figure 2 shows the case that the air temperature, precipitation, river flow discharge, and global solar radiation only in the downstream region are used as variables. The daily averaged value can be reproduced accurately to some extent, but the daily fluctuation is very large (correlation factor R = 0.538, root mean square error (RMSE) value: 2.837).

Next, several explanatory variables were added to reduce daily fluctuations. Figure 3 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. Also, the hourly fluctuation was included by adding + 1h and + 2h data of each element as variables. 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. This means that river water temperature at the lowest reach is not affected by the weather condition at the upper and the middle reach in these rivers.

Finally, Fig.4 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.

4. CONCLUSIONS

We attempted to develop a model to estimate riverine water temperature from the meteorological condition data using a neural network as a kind of AI. Some explanatory variables were added to suppress daily fluctuation in the original case. Then, the daily fluctuation became smaller, but the prediction accuracy was poor. In the further research, we will continue to adjust the explanatory variables and to improve the accuracy by using the other type of NNW that is more suitable for time-series data. And we will try to predict the riverine water temperature using climate change prediction products such as d4PDF and d2PDF, and to adapt it for the pseudo global warming experiment to understand the effects on the riverine and marine environment.

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