How to Predict Seawater Temperature for Sustainable Marine Aquaculture (Student Abstract)

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Abstract

The increasing global demand for marine products has turned attention to marine aquaculture. In marine aquaculture, appropriate environment control is important for a stable supply. The influence of seawater temperature on this environment is significant and accurate prediction is therefore required. In this paper, we propose and describe the implementation of a seawater prediction method using data acquired from real aquaculture areas and neural networks. Our evaluation experiment showed that hourly next-day prediction has an average error of about 0.2 to 0.4 °C and daily prediction of up to one week has an average error of about 0.2 to 0.5 °C. This is enough to meet actual worker need, which is within 1 °C error, thus confirming that our seawater prediction method is suitable for actual sites.

Introduction

The development of transportation technology and the increase in world population has rapidly accelerated the demand for marine products. Global seafood consumption has almost doubled in the past half century and is expected to increase further. However, although demand is increasing, the use of marine resources worldwide has already reached its upper limit and, since around the 1990s, commercial fishing production has been almost constant. Further development is not expected. On the other hand, the aquaculture industry has been growing rapidly, with production increasing by about 10 times over the past 20 years and exceeding commercial fishing production.

One current problem for aquaculture is the damage caused by abnormal water temperatures. To minimize this damage, it is necessary to accurately predict changes in seawater temperature and to appropriately maintain the aquaculture area's environment. Current water temperature prediction is largely dependent on the ability of the workers, requiring a wealth of knowledge and many years of experience. However, with our aging society, the number of skilled workers decreases each year; thus, it is difficult to continue predicting using the current method. A new water temperature prediction method must be established that does not depend on worker experience.

As existing prediction methods, there are some sea surface temperatures and currents prediction(Nakagawa et al. 2018). However, in aquaculture, marine products are mainly grown at water depths of about 2 m to 10 m, so sea water temperatures below the sea surface are important. More specialized to aquaculture, there are methods using buoy(Abe and Wada 2010) and observation devices(Otsuka, Kitazawa, and Ito 2018), but these prediction term is limited like next day only. In addition, there is a need within 1 °C error from actual employees, but the prediction accuracy of these methods is as large as 1 °C error, and it is difficult to use these methods in aquaculture. In this study, we propose a seawater prediction method that uses neural networks to individually learn past data in the aquaculture area and predict water temperatures below sea level for each area.

Multiple-Term Seawater Temperature Prediction Method

Acquisition of Environmental Data

For this study, we selected pearl aquaculture areas in Mie Prefecture as our experimental site and conducted experiments on a total of four places (Gokasho Bay, Matoya Bay, and the back and middle of Ago Bay) (see Figure 1). Water temperature monitoring devices have been present at these farms since 2007 at the points shown in Figure 1, and water temperature is measured continuously. The observed water temperature is periodically transmitted to a server using a cellular phone network and stored in a database.

Seawater Temperature Prediction Model

The whole our prediction model is shown in the Figure 1. In the input layer, seawater temperature data and meteorological data are input. Current seawater temperature is the most important information for prediction, because seawater temperature is difficult to change. Our model can input multiple depths' water temperatures and learn other depth effects. Meteorological data is also important, especially the water temperature near the sea surface is strongly affected. As meteorological data, temperature, wind speed, month and

Figure 1: Observation points

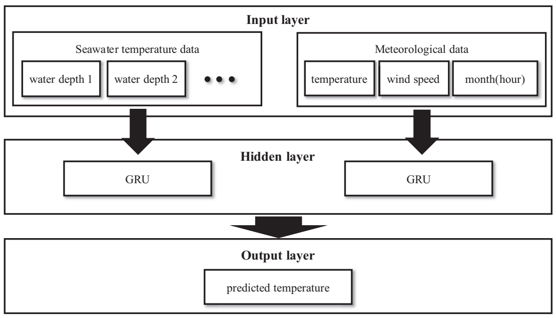

Figure 2: Prediction model

hour are input, these have the strongest impact on seawater temperature change. In the hidden layer, each seawater temperature data and meteorological data is entered in the different Gated Recurrent Unit(Cho et al. 2014). In the output layer, results of hidden layer are converted to predicted water temperature.

In addition, to increase practicality, prediction model is divided into two types, a short-term model that performs hourly predictions until the next day and a long-term model that performs daily predictions for one week ahead. Short-term model can predict detailed seawater temperature and it can be used for detection of timing when seawater temperature changes greatly. Long-term model can predict average water temperature and we can visualize long-term seawater temperature flow with this prediction. This is a standard of future seawater temperature change and used for schedule management.

Experiments

In the experiment, we constructed a prediction model using the sea water temperature data of four pearl aquaculture areas and meteorological data as learning data for 10 years. One year of data not used for learning was used for accuracy verification. Tables 1 and 2 show the mean absolute error of the short-term and long-term prediction, respectively. GRU is our method, RF is the short-term prediction method with RandomForest (Otsuka et al. 2018), and MR is the long-term prediction method with multiple regression (Nakagawa et al. 2018).

Results for the short-term model is about 0.2 to 0.4 °C

Area	Method	0.5 m	2.0 m	5.0 m	8.0 m
Gokasho	GRU	0.385 °C	0.275 °C	0.236 °C	0.245 °C
	RF	1.085 °C	0.991 °C	0.959 °C	0.930 °C
Matoya	GRU	0.385 °C	0.282 °C	0.233 °C	0.263 °C
	RF	1.059 °C	1.057 °C	1.068 °C	1.049 °C
Ago-back	GRU	0.306 °C	0.231 °C	0.219 °C	0.259 °C
	RF	1.053 °C	1.056 °C	1.056 °C	1.083 °C
Ago-mid	GRU	0.237 °C	0.209 °C	0.189 °C	0.139 °C
	RF	1.266 °C	1.256 °C	1.200 °C	1.19 °C

Table 1: Results for short-term prediction

Area	Method	0.5 m	2.0 m	5.0 m	8.0 m
Gokasho	GRU	0.391 °C	0.393 °C	0.416 °C	0.415 °C
	MR	0.511 °C	0.406 °C	0.415 °C	0.455 °C
Matoya	GRU	0.441 °C	0.446 °C	0.469 °C	0.478 °C
	MR	0.537 °C	0.491 °C	0.518 °C	0.517 °C
Ago-back	GRU	0.340 °C	0.360 °C	0.400 °C	0.434 °C
	MR	0.461 °C	0.394 °C	0.405 °C	0.433 °C
Ago-mid	GRU	0.276 °C	0.245 °C	0.238 °C	0.224 °C
	MR	0.300 °C	0.266 °C	0.255 °C	0.274 °C

Table 2: Results for long-term prediction

and long-term model is about 0.2 to 0.5 °C. Since the actual needs of the workers are within 1 °C error, the prediction accuracy is sufficient. Compare with existing methods, short-term prediction error is maximum about 1 °C lower and long-term is maximum about 0.1 °C lower.

Conclusion

In this paper, we presented a method to predict sea water temperatures in aquaculture areas. The proposed method makes it possible for new workers to easily and accurately predict temperatures. In addition, experiments showed that hourly next-day predictions have an average error of about 0.2 to 0.4 °C, and daily predictions up to one week ahead of about 0.2 to 0.5 °C. The results show that the proposed method can predict practically because it is far below the workers' need of 1 °C. In the future, we aim to further improve the prediction accuracy in order to achieve more practical prediction. We will also evaluate other aquaculture areas to demonstrate that the proposed method can be used generally.

References

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