

# Short-range forecast of Shershnevskoie (South Ural) water-storage algal blooms: preliminary results of predictors' choosing and membership functions' construction

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## INTRODUCTION



Short-range, medium-range and long-term forecasting of algal blooms in drinking water reservoirs and other waterbodies is an actual element of water treatment management as it provide information necessary for making rational decisions (Recknagel,1997; Oh et al., 2007; Sene, 2010).

Particularly, Shershnevskoie reservoir - the source of drinking water for Chelyabinsk city (South Ural region of Russia) - is exposed to interannual, seasonal and short-range fluctuations of blue-green alga Aphanizomenon flos-aquae and other dominant species abundance, which lead to technological problems and economic costs and adversely affect the water treatment quality. Therefore during the periods of blooms that's important for managers and decision makers to be prepared to the possible intensive blue-green algae outbreaks.

For this purpose, firstly fuzzy logic and fuzzy artificial neural network patterns for blue-green alga Microcystis aeruginosa (M. aeruginosa) blooms prediction in nearby undrained Smolino lake were developed. These results served as the base to derive membership functions for reservoir forecasting patterns.

## DATA AND METHODS

Time series of dominant species' seasonal abundance, temperature, cloud amount, wind speed, mineralization, phosphate and nitrate concentrations were obtained through field observations held on Smolino lake in the warm season of 2009 and 2011 with time resolution of 2-7 day. For Shershnevskoie reservoir forecasting long-term data of chemical parameters, measured once in a month, data of dominant species abundance, measured fifth in a week and data of water temperature, turbidity, water color, alkalinity, pH, obtained each day, were analyzed.



Time series of data were interpolated and normalized and then cross-correlation analyses was used to reveal potential connections between blue-green algae abundance and other parameters for different sets of data. Designing forecasting models the best fitting parameters with high value of cross-correlation coefficient ( $>0,6$ ) were selected. When loading input variables the time delays for each parameter were taken into account. These delays determined the lead time of the forecast.

## RESULTS

For fuzzy prediction models on the database of 2009 and 2011 membership functions and rules linking M. aeruginosa and paramters values were set up manually using Mamdani algorithm. For fuzzy ANN method of forecasting predictive rules and membership functions were set up automatically using Sugeno algorithm. Developed fuzzy logic rules were good to predict the M. aeruginosa most intensive outbreaks. The best results of modelling are shown in figures bellow.

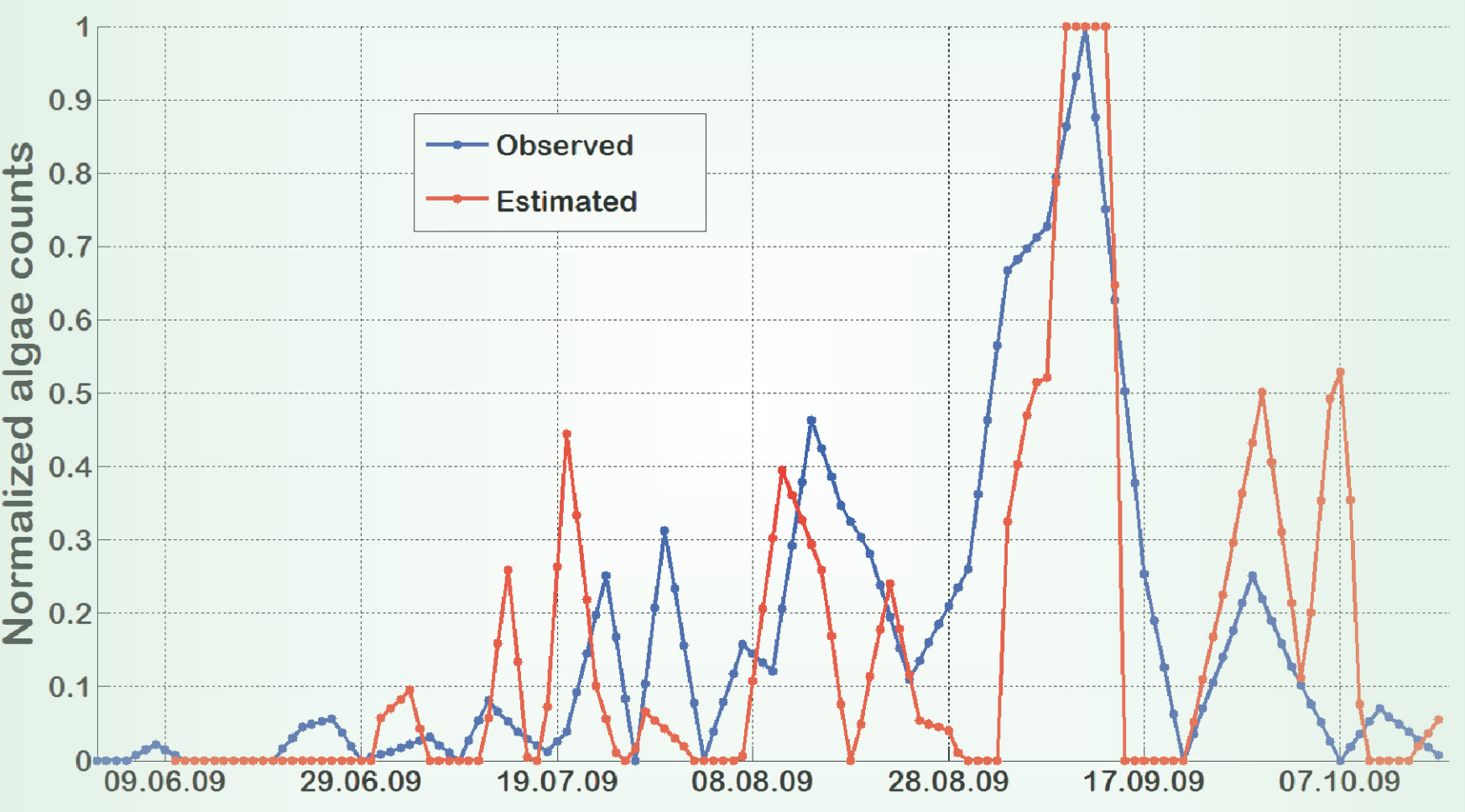


Figure 1. The result of using fuzzy logic to predict M. aeruginosa blooms in 2009. Predictor: P. duplex abundance. Lead time: 6 days

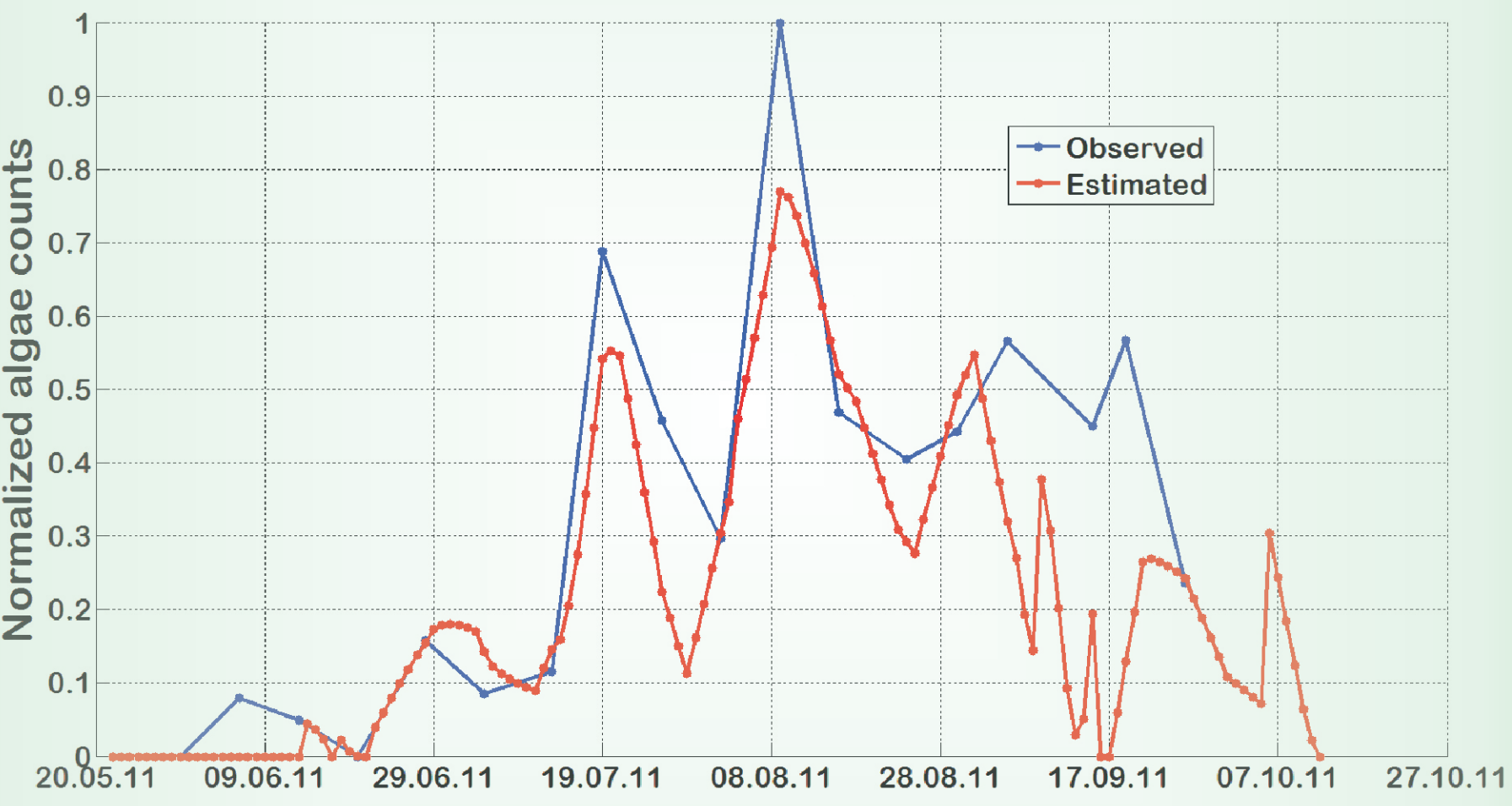


Figure 2. The result of using fuzzy ANN to predict M. aeruginosa blooms in 2011. Predictors: P. duplex abundance and water temperature. Lead time: 23 days

## RESULTS

When designing models to predict outbreaks of M. aeruginosa and Aphanizomenon flos-aquae in Shershnevskoie reservoir in 2012 Sugeno algorithm was used, as there was a large data set for teaching fuzzy ANN. The best result for Aphanizomenon flos-aquae is illustrated in fig. 3.

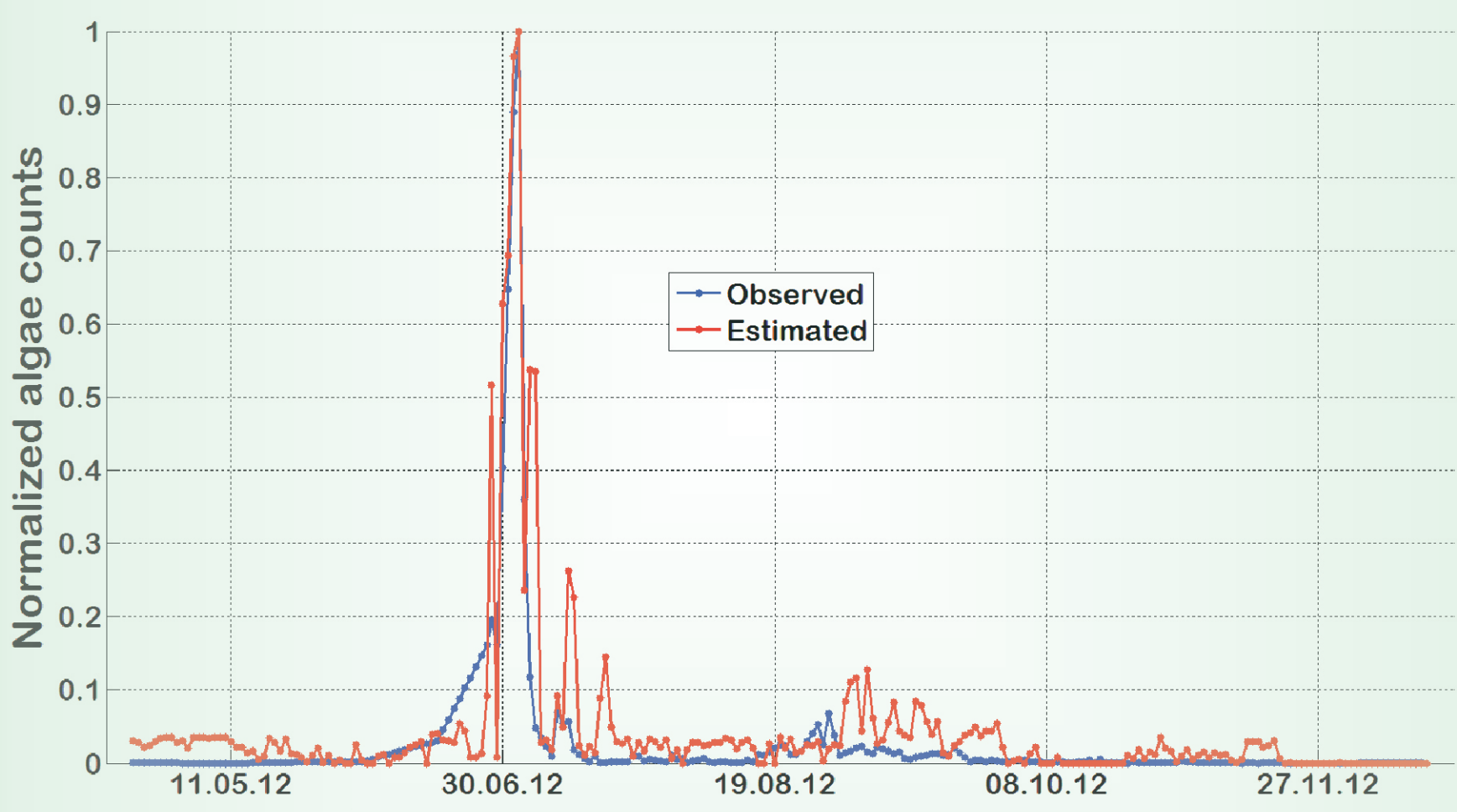


Figure 3. The result of using fuzzy ANN to predict Aphanizomenon flos-aquae blooms in 2012. Predictor: water turbidity. Lead time: 7 days

## CONCLUSIONS

The preliminary results of choosing predictors and first derived models showed that there is a possibility to predict blue-green algae most intensive outbreaks. There are some difficulties connected with the fact that predictors' and algae coherent relations differ each year and change the lead time of the forecast. That's important to use long-term data determining the role of predictors. Anyway good forecast product can be useful for decision-making when operating water treatment systems (see diagram above).

## REFERENCES

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## RESULTS

Finally, data sets of chemical, hydrobiological and some physical parameters collected monthly over the period of 5 years (2009-2013) were used to predict outbreaks of blue-green algae. The best result for M. seruginosa is shown in fig. 4.

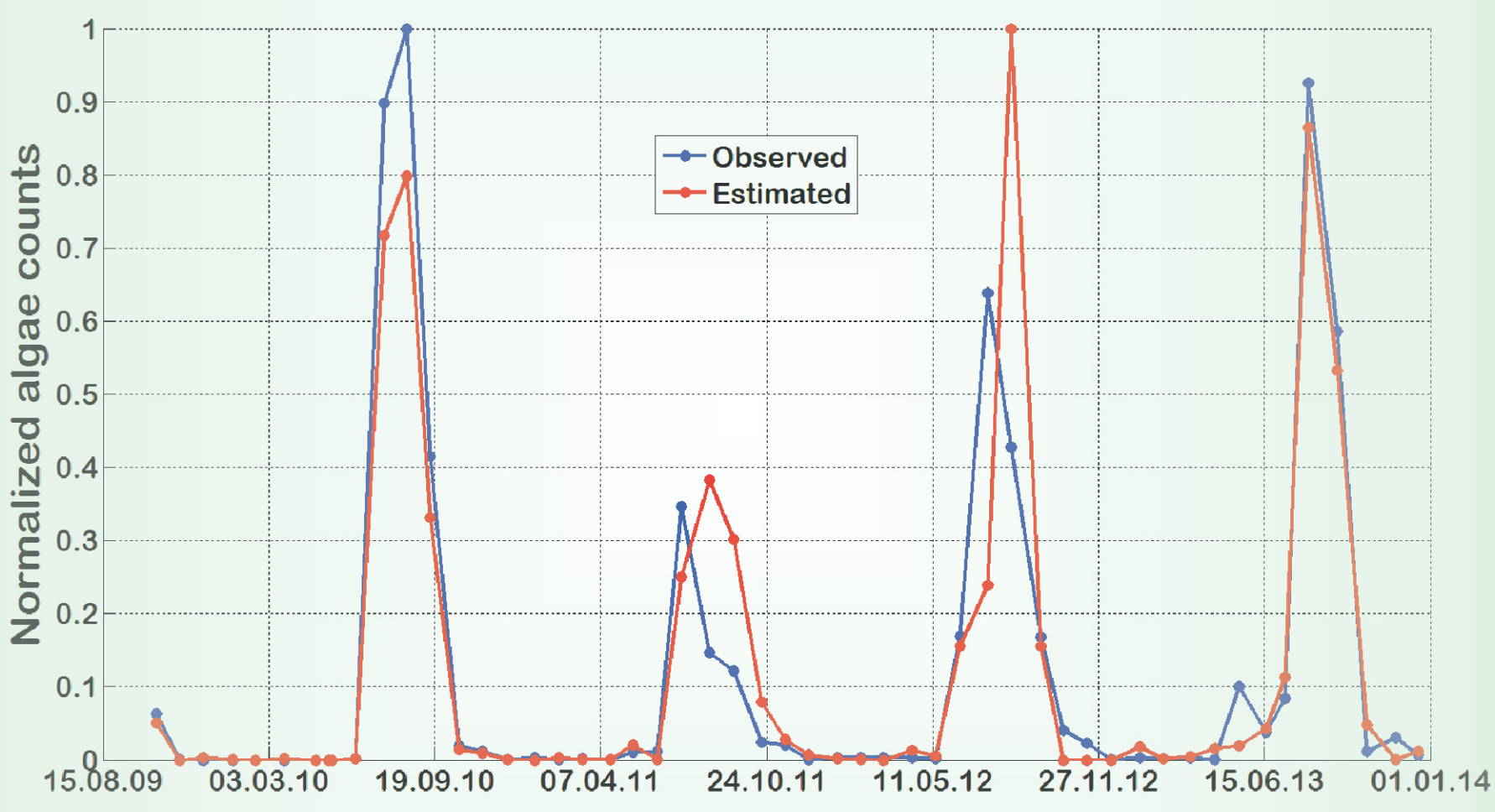
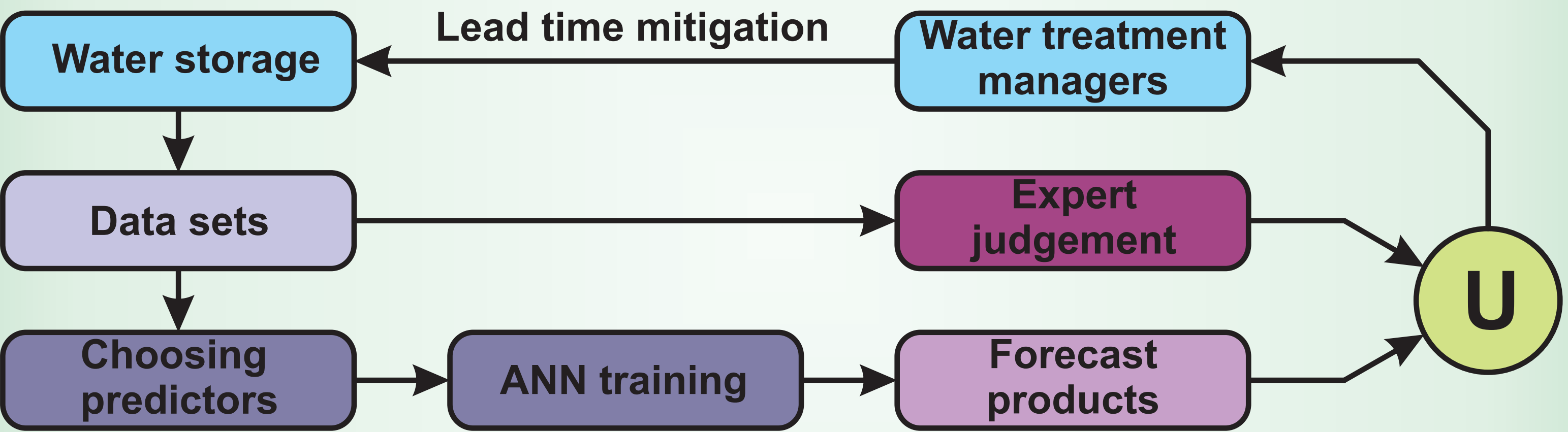


Figure 4. The result of using fuzzy ANN to predict M. aeruginosa blooms in 2009-2013. Predictors: water temperature, concentration of  $O_2$ . Lead time: 1 month



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