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VIRTUAL SENSOR FOR AMMONIA ESTIMATION IN AQUACULTURE TECHNOLOGICAL WATER FROM CAMBODIA

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Abstract

In Cambodia, the aquaculture sector registers as one of the fastest-growing food sectors, with a mean annual growth of more than 18% between 2002 and 2020. The main challenge associated with the intensification of aquaculture is the discharge of untreated effluents, which contain large amounts of organic matter, nutrients, minerals, and other chemicals. Among these, ammonia (NH_3) is of the highest interest to monitor and measure in the technological water since it directly influences the survival and growth performance of the fish biomass. At the same time, the discharge of aquaculture wastewaters, containing high concentrations of ammonia, can generate water eutrophication in the natural aquatic environments receiving the effluents. The present study aimed to develop a virtual sensor capable of estimating the concentration of NH_3 in the technological water of a typical earthen aquaculture pond from Phnom Penh – Cambodia. Multiple decision tree algorithms were employed for the prediction analysis and the accuracy was established based on RMSE (root mean square error) and R squared values.

Key words: *soft-sensor, ammonia, aquaculture, Cambodia.*

INTRODUCTION

Mekong River (MR) is one of the largest rivers in the world, with a total length of 4800 km (Meur et al., 2021). The Lower MR supports highly valuable economic activities such as fisheries and aquaculture (Sor et al., 2021). The water resources provided by the Lower MR are crucial for the well-being of the riparian communities from Cambodia, Vietnam Laos, and Thailand respectively (Chea et al., 2016).
For instance, in Cambodia, the aquaculture sector registers one of the fastest growth among all the food sectors, with a mean annual growth of more than 18% between 2002 and 2020 (Larson et al., 2023). Aquaculture in Cambodia is dominated by fish farming in freshwater, in small-scale production systems such as cage culture and pond culture respectively (Larson et al., 2022). Fish and derived fish products account for 76% of the total animal protein intake of Cambodian people, with an average fish consumption of 63 kg/person/year (Chea et al., 2023). In 2018, the total annual fish production was 910,153 tons, with inland capture fisheries accounting for 59%, followed by aquaculture (28%) and marine capture fisheries (13%) (Chea et al., 2023). In terms of economic importance, Cambodia's total aquaculture sector value was $200 million in 2022 and is forecasted to reach $500 million by 2027. In this context of Cambodia's intensification of aquaculture, special care should be paid to water quality. Water quality directly influences growth performance and aquatic livestock production (Nguyen et al., 2022). The main challenge associated with the intensification of the aquaculture sector is the discharge of untreated effluents, which contain large amounts of organic matter, nutrients, minerals, and other chemicals. Among these, ammonia (NH_3) is of the highest interest to monitor and measure in the technological water since it directly influences the survival and growth performance of the fish biomass. At the same time, the discharge of aquaculture wastewaters, containing high concentrations of ammonia, can generate water eutrophication in

the natural aquatic environments receiving the effluents. Therefore, continuous monitoring of water physicochemical parameters is mandatory to maintain the optimum and safe levels of various indicators (Hong & Giao, 2022). Assessment of water quality is a practice that involves high financial resources allocated to specialized human resources and expensive equipment, and reagents respectively. During the last years, the development of the Internet of Things (IoT), artificial intelligence (AI) technologies, and predictive modeling techniques such as machine learning have become assistance for monitoring water quality in different aquatic ecosystems (Ahmed et al., 2019; Sankaran, 2019). The objective of virtual sensors is to identify mathematical connections between the variables within an aquatic ecosystem and to develop models able to predict the parameters that are difficult to measure based on those that are easy to measure (Zhou et al., 2022).

The present study aimed to develop a virtual sensor capable of estimating the concentration of NH_3 in the technological water of a typical earthen aquaculture pond from Phnom Penh – Cambodia. Multiple decision tree algorithms were employed for the prediction analysis and the accuracy was established based on RMSE (root mean square error) and R squared values.

MATERIALS AND METHODS

The water quality data was obtained daily, based on *in situ* measurements and laboratory analysis during April and December 2023. The measurements were determined in the technological water of a nursery pond from the National Aquaculture Research and Development Institute (NARDI) – Phnom Penh, Cambodia. The following physicochemical parameters were analyzed: dissolved oxygen (DO), temperature, pH, electroconductivity (EC), and ammonia (NH_3). Temperature, DO, EC, and pH were measured using portable sensor devices, while ammonia (NH_3) was calculated based on the HN_4 concentration value determined spectrophotometrically.

The database was further used to predict the value of NH_3 in the technological water based on the values of DO, EC, pH, and temperature respectively. Multiple decision tree algorithms were employed (random forest, decision tree, and XGBoost) for the prediction analysis and the accuracy was established based on RMSE (root mean square error) and R-squared values. As well, a multi-linear regression model was used in the prediction analysis to compare accuracy.

RESULTS AND DISCUSSIONS

1. *Random forest analysis*

The RF analysis for the prediction of NH_3 generated an R-squared of 0.62 and an RMSE of 0.07 (Figures 1 and 2).

The feature importance highlighted that the most important variable for the prediction of NH_3 was temperature, followed by pH (Figure 3). The least important variable in the prediction analysis was EC (Figure 3).

2. *Decision tree analysis*

The decision tree analysis for the prediction of NH_3 generated an R-squared of 0.55 and an RMSE of 0.078 (Figures 4 and 5).

The feature importance highlighted that the most important variable for the prediction of NH_3 in the decision tree analysis was temperature, followed by pH (Figure 6). The influence of DO and EC in the prediction analysis through the decision tree technique was limited.

3. *XGBoost analysis*

The HGBoost analysis for the prediction of NH_3 generated an R-squared of -0.01 and an RMSE of 0.11 (Figure 7). This technique was not performant in the prediction of HN_3.

4. *Multi-linear regression model*

The first step in the multi-linear regression analysis was to test the collinearity of the data (Figure 8), to ensure there is no overlaying.

As can be seen in Figure 8, the variance inflation factor was below 10, which indicates that the data is not overlaying.

The multi-linear regression analysis for the prediction of NH_3 generated an R-squared of 0.5 and an RMSE of 0.08 (Figures 9 and 10).

As can be observed in Figure 10, the significant parameters in the prediction NH_3 were temperature, pH, and EC, while DO was not significant in the prediction analysis.

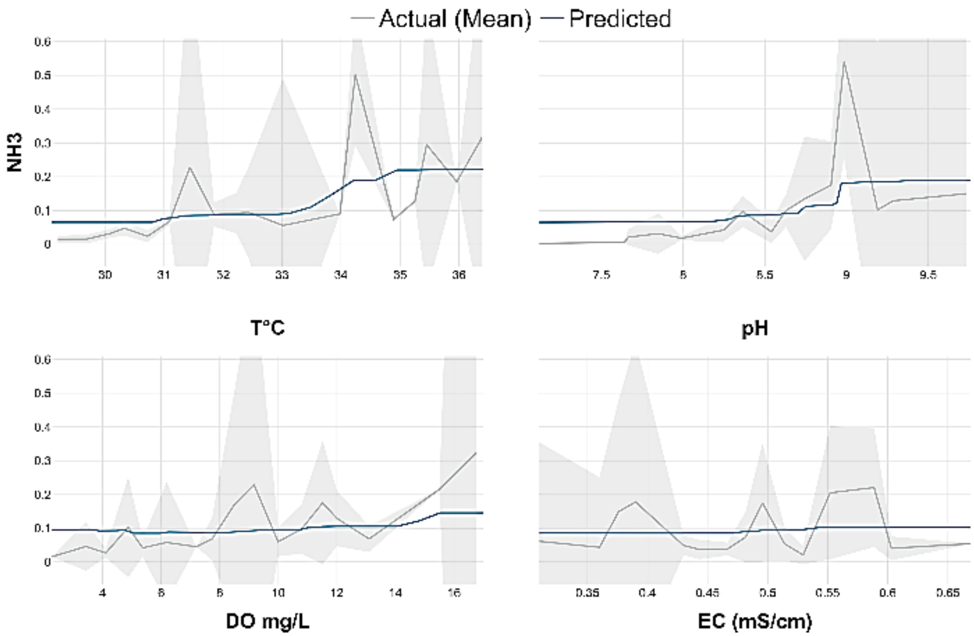

Figure 1. Performance of RF analysis for the prediction of NH_3

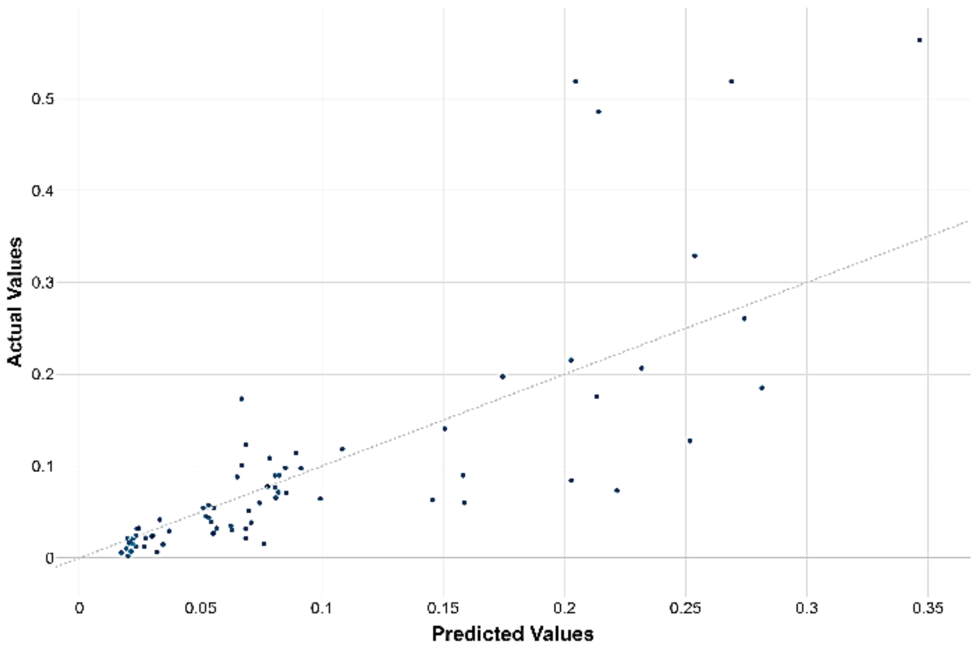

Figure 2. Performance of RF analysis for the prediction of NH_3

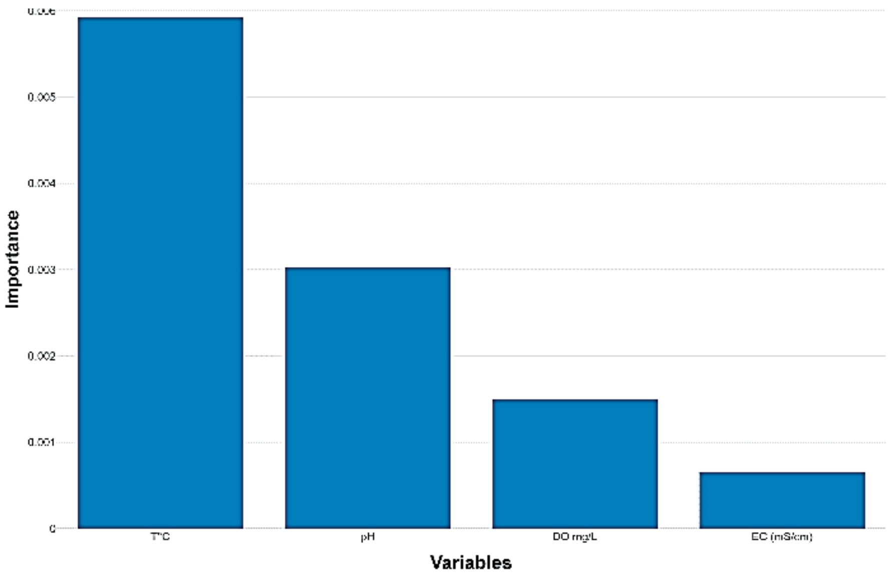

Figure 3. The FI of dependent variables in the RF analysis

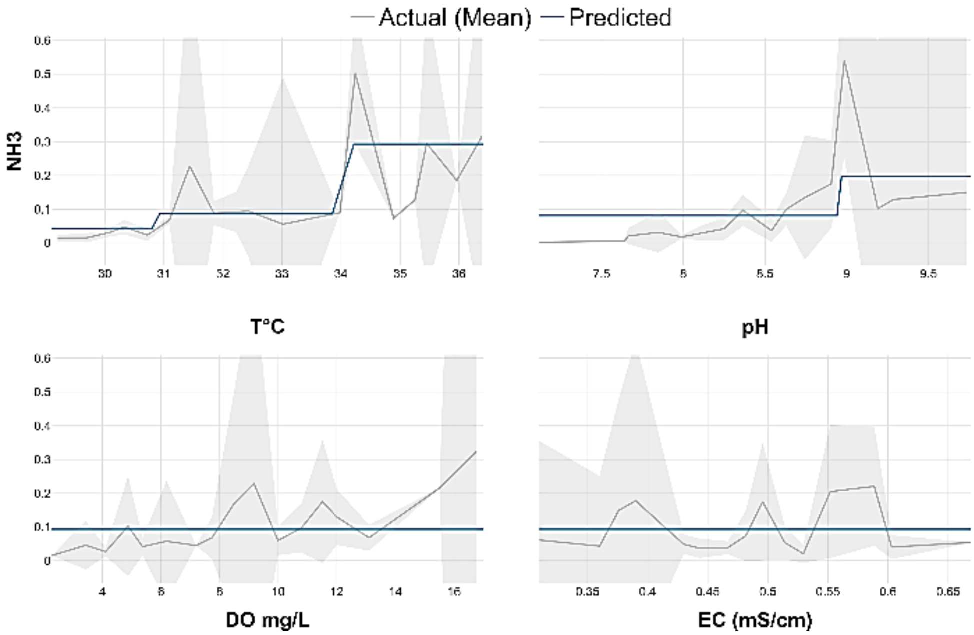

Figure 4. Performance of decision tree analysis for the prediction of NH_3

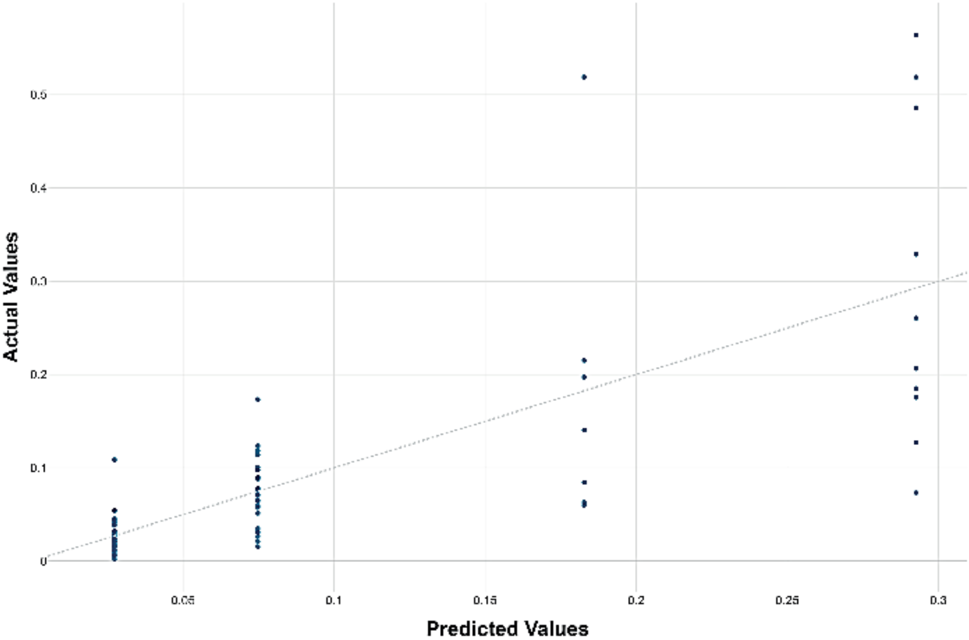

Figure 5. Performance of decision tree analysis for the prediction of NH_3

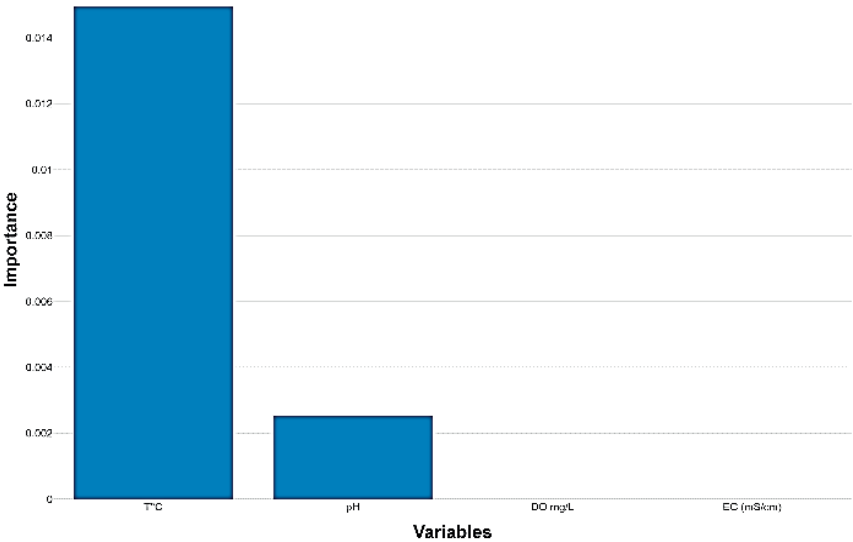

Figure 6. The FI of dependent variables in the decision tree analysis

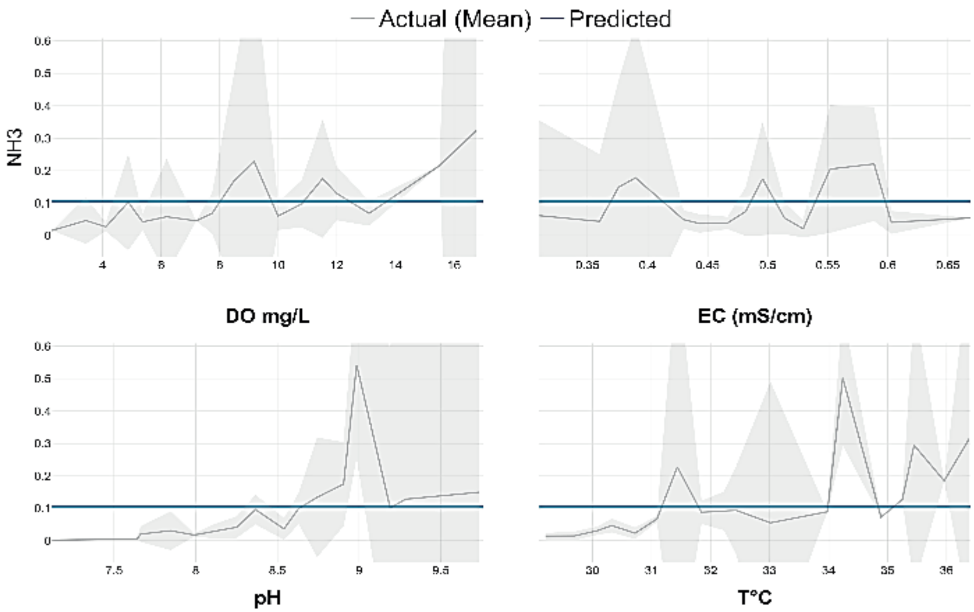

Figure 7. Performance of HGBoost analysis for the prediction of NH_3

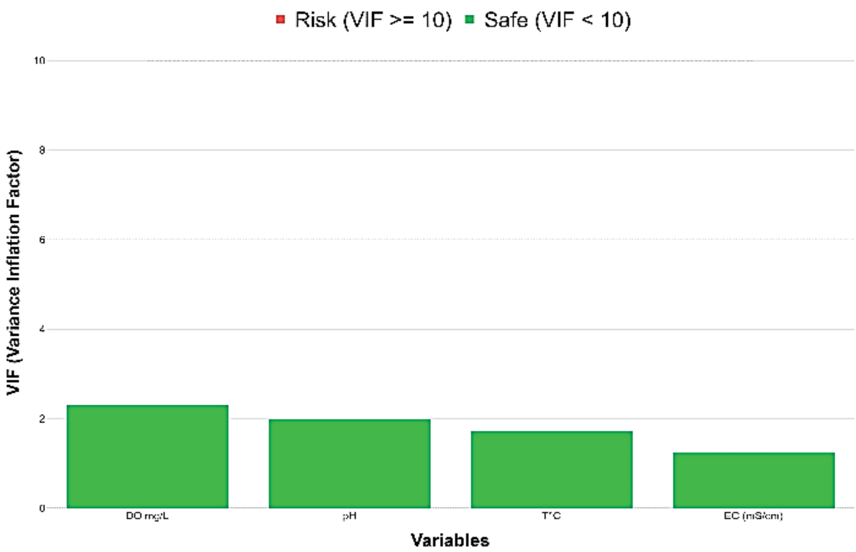

Figure 8. Data collinearity

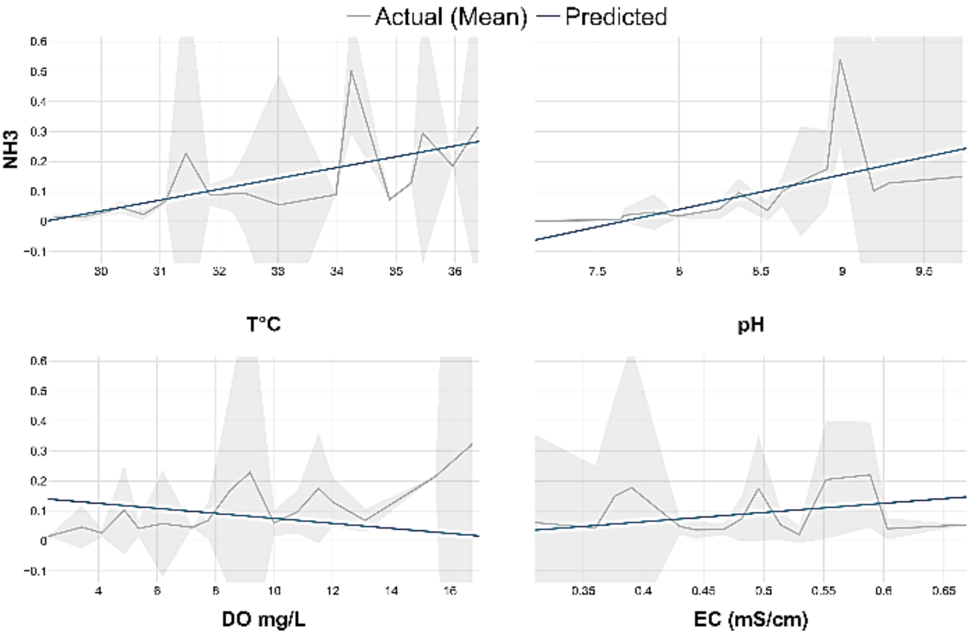

Figure 9. Performance of multi-linear regression analysis for the prediction of NH_3

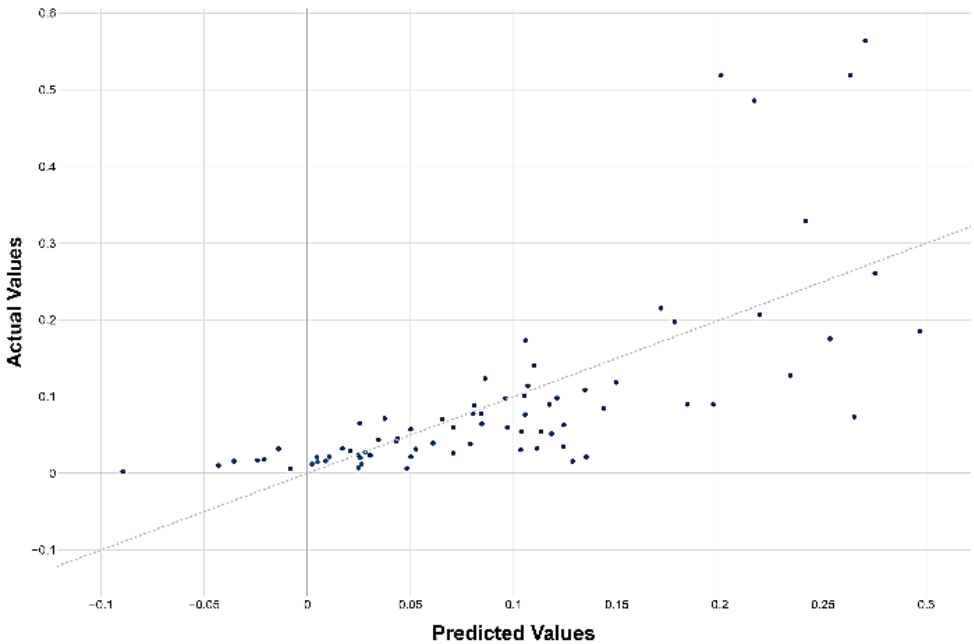

Figure 10. Performance of multi-linear regression analysis for the prediction of NH_3

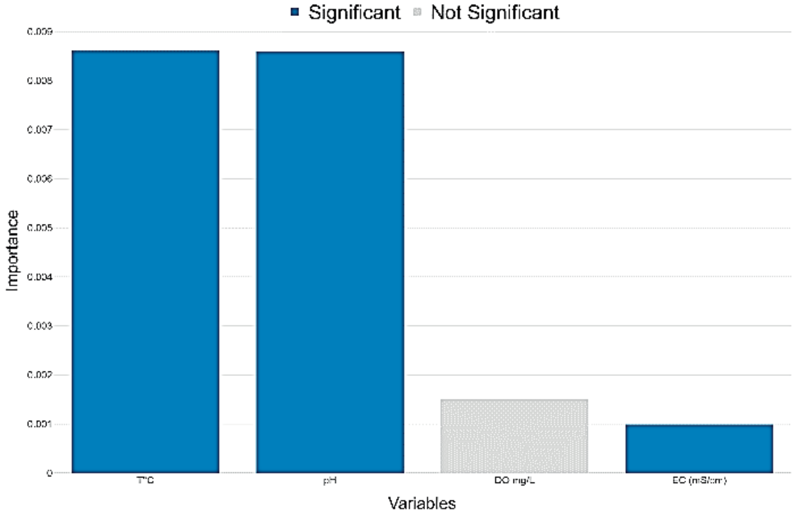

Figure 11. The FI of dependent variables in the multi-linear regression analysis

CONCLUSIONS

The present study demonstrated that the use of aquatic soft sensors for the determination of ammonia compounds in aquaculture facilities is feasible. Random forest performed the best in the prediction analysis, followed by the multi-linear regression analysis. This solution can be applied not only in areas lacking financial resources but also in more developed areas, thus increasing economic and environmental sustainability.

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REFERENCES

Ahmed, U., Mumtaz, R., Anwar, H., Mumtaz, S., & Qamar, A.M. (2019). Water quality monitoring: From conventional to emerging technologies. *Water Supply*, *20*(1), 28–45. https://doi.org/10.2166/ws.2019.144

Chea, R., Ahsan, D., García-Lorenzo, I., & Teh, L. (2023). Fish consumption patterns and value chain analysis in north-western Cambodia. *Fisheries Research*, *263*, 106677. https://doi.org/10.1016/j.fishres.2023.106677

Chea, R., Grenouillet, G., & Lek, S. (2016). Evidence of water quality degradation in lower Mekong Basin revealed by self-organizing map. *PLOS ONE*, *11*(1), e0145527. https://doi.org/10.1371/journal.pone.0145527

Hong, T.T.K., & Giao, N.T. (2022). Analysis of surface water quality in upstream province of Vietnamese Mekong Delta using Multivariate Statistics. *Water*, *14*(12), https://doi.org/10.3390/w14121975.

Larson, S., Hoy, S., Thay, S., & Rimmer, M.A. (2023). Sustainable and inclusive development of finfish mariculture in Cambodia: Perceived barriers to engagement and expansion. *Marine Policy*, *148*.

Larson, S., Rimmer, M.A., Hoy, S., & Thay, S. (2022). Is the marine finfish cage farming value chain in Cambodia inclusive? *Aquaculture*, *549*, 737782.

Meur, M.L., Phu, V.L., Gratiot, N., Meur, M.L., Phu, V.L., & Gratiot, N. (2021). What is the future of the Lower Mekong Basin struggling against human activities? A Review. In *River Deltas Research—Recent Advances*. IntechOpen.

Nguyen, T.G., Phan, K.A., & Huynh, T.H.N. (2022). Major concerns of surface water quality in south-west coastal regions of Vietnamese Mekong Delta. *Sustainable Environment Research*, *32*(1).

Sankaran, M. (2019). *Why wastewater quality monitoring matters*. Wastewater Digest.

Sor, R., Ngor, P.B., Soum, S., Chandra, S., Hogan, Z.S., & Null, S.E. (2021). Water quality degradation in the Lower Mekong Basin. *Water*, *13*(11).

Zhou, M., Zhang, Y., Wang, J., Shi, Y., & Puig, V. (2022). Water quality indicator interval prediction in wastewater treatment process based on the improved BES-LSSVM Algorithm. *Sensors*, *22*(2).