Exploring the Impact of Coastal Water Quality Parameters on Chlorophyll-*a* near Cyprus with the use of Artificial Neural Networks

Hadjisolomou Ekaterini [(1)], Antoniadis Konstantinos [(2)], Thasitis Ioannis[(2)], Abu-Alhaija Rana [(3)], Herodotou Herodotos[(1)], Michaelides Michalis[(1)]

[(1)] Department of Electrical Engineering, Computer Engineering and Informatics, Cyprus University of Technology, 3036 Limassol, Cyprus
e.hadjisolomou@cut.ac.cy, herodotos.herodotou@cut.ac.cy, michalis.michaelides@cut.ac.cy

[(2)] Department of Fisheries and Marine Research, Ministry of Agriculture, Rural Development and the Environment, 2033 Nicosia, Cyprus
kantoniadis@dfmr.moa.gov.cy, IThasitis@dfmr.moa.gov.cy

[(3)] Cyprus SubSea Consulting and Services (CSCS) Ltd, 34A Paragogikotitas St. Lakatamia, 2326 Nicosia, Cyprus
rana.a@cyprus-subsea.com

Abstract

In this study, sea surface chlorophyll-a (Chl-*a*) levels are modelled with the use of artificial neural networks (ANNs) in an attempt to improve the understanding of coastal eutrophication, a major environmental problem of the modern world. Typical water quality parameters such as water temperature, nitrogen species, phosphorus, pH, salinity, electrical conductivity, and dissolved oxygen, served as the model's inputs. These parameters and Chl-*a* were measured for several locations near the coastline of Cyprus (located in Eastern Mediterranean) during the period 2000-2014, and were used to build an ANN model. Generally, the coastal water quality of Cyprus is good and the whole area is characterized as ultra-oligotrophic, with very few recorded eutrophication events. However, some of the monitoring stations have been strategically positioned in suitable sites for monitoring conditions related to anthropogenic pressure (e.g., due to aquaculture or nearby industrial units). Additionally, the Eastern Mediterranean area is one of the most affected areas by climate change and the associated water temperature increase. The ANN managed to predict with good accuracy the Chl-*a* levels ($RMSE$=0.161 and R=0.873). Sensitivity analysis was also performed, where the input parameters were perturbed by a small amount (8% in our case) and the impact of these perturbations was simulated, leading to several useful results. Specifically, the water temperature perturbation resulted in an increase of Chl-*a* levels by over 123%, which is especially worrisome when considering the effects of global warming on eutrophication. Analogous behavior was observed for the nutrients' perturbations, where a significant increase of Chl-*a* was also calculated. These findings indicate that the Cyprus coastal environment is fragile and prone to eutrophication under anthropogenic pressure and climate change. The constructed ANN model can serve as a management tool, to maintain the good environmental status of the Cyprus coastal waters.

Keywords: Coastal Water Eutrophication; Chlorophyll-a; Water Temperature; Artificial Neural Networks; Sensitivity Analysis

1. INTRODUCTION

Eutrophication should be considered among the significant problems facing the world today, as it is responsible for the degradation of water quality in many freshwater, coastal, and marine ecosystems around the globe (Hadjisolomou et al., 2016; Vigouroux et al., 2021). Because coastal waters are major providers of economical services (e.g., tourist activities, aquaculture), eutrophication has severe socioeconomic implications that threaten humans' well-being, particularly in areas of the world economically dependent from tourism, such as Cyprus. Given the anticipated impact of climate change on the quality/availability of water resources, as well as the water quality degradation due to population growth, mitigating the adverse effects of eutrophication is becoming a top priority for managing authorities around the world. The main cause of surface water eutrophication is the increased nutrients (phosphorus and nitrogen), that enter the water bodies through anthropogenic activities, such as sewage discharge and diffuse pollution caused by agricultural fertilizers (Ferreira et al, 2011). Lately, climate change has been highlighted as an additional threat for coastal ecosystems, mainly because the temperature increase is expected to boost eutrophication and the occurrence of algal blooms, especially in the Eastern Mediterranean basin (Hadjisolomou et al, 2018).

In many cases, eutrophication is responsible for the occurrence of Harmful Algal Blooms (HABs), which pose an important threat for aquatic life and the function of multiple related economic services (Mishra et al., 2021). Water sports and recreational activities such as swimming, the consumption of seafood, and drinking water contaminated with toxins, can cause severe human illness. About 60,000 intoxication incidents, with an overall mortality rate of 1.5%, are reported globally per year because of algal toxins (Ferrante et al., 2013). Additionally, the impact of eutrophication on aquaculture can be a serious threat to the Cypriot economy. As it is well known, eutrophication may become responsible for massive fish kills (Ram et al., 2014), but also can degrade water quality thus stimulating disease outbreaks to enclosed fish populations (with subsequent capital loss) and increased operational costs due to higher rates of cage net fouling (Sliskovis et al 2011).

Not surprisingly, scientists are developing new tools and methods for improving the monitoring of water quality, like the use of automated sensors (Pule et al., 2017). In addition, they employ advanced modelling techniques and algorithms for creating novel forecasting schemes, that can provide early warning against eutrophication and algal blooms (e.g., Guo et al., 2021), thus minimizing the impact on human societies and the aquatic environment (Hadjisolomou et al, 2021).

In this study, we explore the use of an Artificial Neural Network (ANN) as a modelling tool to predict the chlorophyll-a (Chl-*a*) levels for the coastal waters of Cyprus. Specifically, measurements from selected points/sampling stations of interest around the coastline of Cyprus (e.g., aquaculture stations, tourist areas, industrial areas, ecological sensitive areas) were used for training and validating the model. The developed ANN model can predict the Chl-*a* concentration with high accuracy, which makes it appropriate for becoming a spherical/holistic approximator regarding the trophic status of the Cyprus coastal and marine waters. Moreover, it can act as the basis for the development of management tools for eliminating the impact of anthropogenic activities (related mainly with nutrients release) and in accordance with climate change. Note that the fact that the Cyprus coastal and marine waters are characterized as ultra-oligotrophic, makes this particularly interesting. Additionally, since Chl-*a* is a major regulator of biological processes in the marine environment, a validated Chl-*a* model can also facilitate several marine organisms' studies, acting as a variable with both explanatory (e.g., population biomass studies), as well as prediction capabilities (e.g., species distribution/habitat models). To the best of our knowledge, this is the first ANN modelling study of Chl-*a* conducted for the coastal waters of Cyprus.

2. METHODOLOGY

2.1 Study Area and Data

The used data set contains measurements of surface environmental parameters obtained from 49 coastal stations near Cyprus (Figure 1), with different anthropogenic impact/activities (aquaculture, nearby industrial units), as monitored by the Department of Fisheries and Marine Research (DFMR) of the Cyprus Republic. The island of Cyprus is located in the Levantine Basin - Eastern Mediterranean, which is one of the most oligotrophic seas in the world, characterized by very low nutrient availability and hence very low primary production (Tselepides et al., 2000). In addition to its ultra-oligotrophism, Levant's Sea is characterized by high temperatures ranging yearly from 16 °C in the winter up to 26 °C in the summer period. Moreover, the evaporation and salinity are high (yearly average salinity of Eastern Mediterranean exceeds 37.5 psu, while average salinity of coastal waters of Cyprus is 39.1 psu); and the inflow of fresh water is very limited due to the absence of large rivers (Antoniadis et al., 2020) and extensive damming in the area (Skliris et al, 2007).

Figure 1. Satellite map of the Cyprus Republic in the Eastern Mediterranean with the monitoring stations marked in green color.

Cyprus, as a Member State of the European Union, must implement several Directives such as the Water Framework Directive 2000/60/EC, the Marine Strategy Framework Directive 2008/56/EC, the Nitrates Directive 91/676/EEC, etc. Also, Cyprus is a Contracting Party to the Barcelona Convention for the protection of the Mediterranean Sea. For the implementation of all the above, DFMR has set a network of sampling stations around Cyprus that is used for many years for the gathering of data used in the assessment of the marine environmental status. More details regarding the stations and the data sampling process can be found in the technical report by Antoniadis et al. (2020).

The data considered for this study includes 681 measurements collected sporadically (no regular time intervals) from the above sampling stations (recall Figure 1) between the years 2000-2014, for the following environmental parameters: nitrogen species (NH_4^+, NO_2^-, NO_3^-); ortho-phosphates (PO_4^{3-}); salinity; dissolved oxygen (DO); pH; electrical conductivity (EC); water temperature (WT); and Chl-*a*.

2.2 ANN Theory

ANNs are inspired by the ability of human beings to perform well complex tasks through the processing of the biological neural system (Han et al., 2012). A simplified definition of the ANN, is that an ANN can be considered as a computing system composed of a highly interconnected set of simple information processing elements (units), analogous to a biological neuron (Sarkar and Pandey, 2015). The aim of an ANN is to create a data driven model which can generalize and produce accurate outputs, even from data that it hasn't seen before (Hadjisolomou et al., 2016).

A commonly used ANN in water quality modelling is the feed-forward Multi-Layer Perceptron (MLP) with the back-propagation training algorithm (Maier and Dandy, 2000). A feedforward ANN has at least three layers. The input layer that imports the input parameters to the network, then one or more hidden intermediate layers, and lastly the output layer that produces the result. Each layer consists of neurons, also called nodes. For every neuron there is a synaptic weight that connects the specific neuron with every neuron of the next layer. Aggregation is performed at every neuron using its weighted inputs from the previous layer and an output is generated through a transfer (or activation) function (Dedecker et al., 2004). The output value of the *j*-th neuron (o_j) is given by the following equation:

$$o_j = f(u_j), \qquad [1]$$

where,

$$u_j = \sum w_{ij}\, x_i + z_j, \qquad [2]$$

f is the transfer function, x_i is the input from the i-th neuron belonging to the immediate previous layer, w_{ij} is the synaptic weight that connects x_i with the j-th neuron, and z_j is a bias term. The output of each neuron is computed and propagated through the next layer until the last layer and the network output is compared with the given output. During this learning procedure, the synaptic weights are readjusted to minimize an error function, usually the mean square error. The ANN's training process is repeated until the ANN produces reliable output values for the unseen (test set) input data (Lee et al., 2013). The application of the *k*-fold cross validation method is a tactic often used to avoid ANN's overfitting (Hadjisolomou et el., 2021). Based on the *k*-fold cross validation method, the data is first divided into *k* equal folds and then the ANN model is cross validated *k* times; each time using a different *k*-th fold for testing and the remaining *k-1* folds for training the model. The optimal *k*-value can be decided based on an evaluation process for which the robustness and reliability of the constructed ANN is assessed (Goethals et al., 2007). A detailed procedure for deciding the optimal *k*-value is described in the study of Hadjisolomou et al., (2021).

The ANNs are evaluated using a variety of performance indices (Salami Shahid and Ehteshami, 2016; Gebler et al., 2020; Hadjisolomou et al., 2016). Popular metrics include the Root Mean Square Error (*RMSE*) and the correlation coefficient (*R*) as given below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(o_i - s_i)^2}{n}} \qquad [3]$$

$$R = \frac{\sum_{i=1}^{n}(o_i - \bar{o})(s_i - \bar{s})}{\sqrt{\sum_{i=1}^{n}(o_i - \bar{o})^2 (s_i - \bar{s})^2}} \qquad [4]$$

In the above set of equations, o_i is the observed value; s_i the simulated value; n the number of observations; the term $\bar{o}$ is the average observed value; and the term $\bar{s}$ is the average simulated value.

The perturbation method can measure the effect / sensitivity of an input variable's small change (i.e., perturbation) on the ANN's output (Muttil & Chau, 2007). The mathematical formula measuring the Sensitivity (%) for a specific input is given by Lee et al. (2003) as:

$$\text{Sensitivity (\%)} = \frac{1}{N_P}\sum_{i=1}^{N_p}\left(\frac{change\ in\ output\ (\%)}{change\ in\ input\ (\%)}\right)_i \times 100, \qquad [5]$$

where N_p is the number of patterns (samples) constructed with inputs and corresponding outputs from the training set.

3. RESULTS

European Commission (EC) has set different limits for eutrophication across all seas, with the collaboration of the Member States, based on their data and after inter-calibration exercises. The decision 2008/915/EC pursuant to Directive 2000/60/EC, includes the limits for excellent, good, and moderate status of coastal waters based on different types of waters that have been inter-calibrated. Based on the results, which relate to geographic areas within the types as described in the technical report, three main categories/clusters corresponding to Chl-*a* levels are found and used for the needs of this modelling study: Cluster 1 (C1) corresponds to Chl-*a* values less than 0.1 (μg/l); Cluster 2 (C2) corresponds to Chl-*a* values between 0.1 (μg/l) and 0.4 (μg/l); and Cluster 3 (C3) corresponds to Chl-*a* values over 0.4 (μg/l). C1 is characterized by excellent (high) water quality; C2 is characterized by good water quality; and C3 is characterized by moderate water quality.

The monitored parameters were examined for collinearity using the Pearson correlation coefficient (r), but no strong correlation existed (r < 0.70). This is a widely used procedure for reducing the number of ANN's inputs and consequently, the model's complexity (Gebler et al., 2020). Therefore, the DO, pH, WT, EC, salinity, NH_4^+, NO_2^-, NO_3^- and PO_4^{3-} served as the ANN's input parameters, while the output was Chl-*a*. MATLAB was used for the ANN's development.

An ANN with a 9-8-1 topology was used for the needs of this modelling study, since it produced the best results among several other tested-candidate topologies following the trial-and-error procedure (Li et al., 2020). All the data was first normalized prior to applying to the ANN model; for the Chl-*a* parameter, a log-transformation was also applied before normalization due to the wide range of Chl-*a* values observed in our dataset (Scardi and Harding, 1999). The k-fold cross validation method was applied with k=30, as this value in our case produced the most accurate results. Even though most modelling studies in the related literature typically use k=10 or k=5 to produce good modelling results (Olden et al., 2008; Deng et al., 2021), other k values are also possible; for example, Chang et al. (2015) in their ANN modelling study used k=14. The generated ANN model is evaluated both as a regressor for predicting Chl-*a* values of test data as well as a classifier for predicting the category (C1-C3) of each sample.

For the implemented ANN model, the graphical representation of the real data points against the simulated data is illustrated in Figure 2. It is clearly observed that the real data are in good agreement with the predicted values. It must be noted that almost all Chl-*a* values are below 1.3 μg/l with the exception of a single measurement (sample no. 673) which is over 3.5 μg/l. However, even for this case, the ANN managed to produce an identical output value. This indicates that the created ANN model is a good predictor of Chl-*a*, not only for normal measurements but even for atypical / extreme values as well. The performance of the proposed ANN is given by *RMSE*=0.161 and R=0.873. Note that the predicted output corresponds to the averaged results of the k=30 associated ANNs. From both of these indices, it becomes apparent that the created ANN is a reliable predictor and can simulate the Chl-*a* levels with good accuracy.

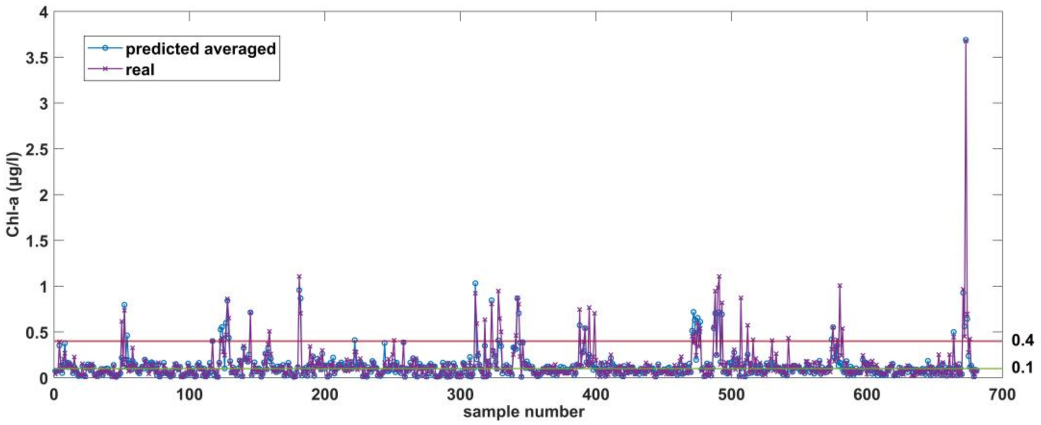

Figure 2. Graphical representation of the real measurements (violet x's) vs. the predicted averaged / simulated values (blue circles) of Chl-*a* levels. The green line indicates the 0.1(μg/l) threshold between excellent (C1) and good (C2) Chl-*a* values, while the red line indicates the 0.4(μg/l) threshold between good (C2) and moderate (C3) Chl-*a* values.

Figure 3 shows the classification performance of the ANN for the three water quality clusters as defined above (i.e., C1: excellent, C2: good, C3: moderate). From the displayed confusion matrix, it becomes apparent that the proposed ANN is able to correctly classify most of the Chl-*a* values with an overall accuracy of 85.3%.

In addition, the percent of true positives (i.e, the proportions of correctly predicted Chl-*a* values) are high for all clusters, with 92.8% for C1, 76.6% for C2 and 84.2% for C3. This is particularly impressive for the C3 category that has a limited number of true samples (51). Note that even when the predicted values are incorrect, they usually fall in the next cluster. For example, out of the 25 false positives for C1, 23 fall under C2 and only 2 under C3. Moreover, all 6 of the false positives for C3 fall under C2 and none under C1. This is particularly important, as it gives an assurance that the predicted value will be correctly interpreted by the relevant authorities and not raise any unnecessary alarms, thus confirming the efficacy of the proposed ANN as a reliable predictor for eutrophication control.

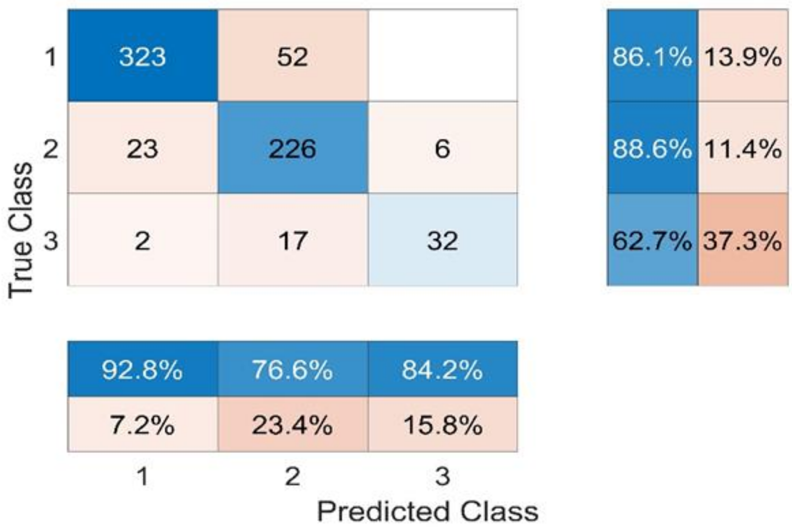

Figure 3. The confusion matrix for the three water quality classes (C1-C3) showing the correctly classified (blue shades) vs. the misclassified (pink shades) of the true and predicted Chl-*a* values.

Sensitivity analysis was performed following the perturbation method, where the input parameters were perturbed / varied by a small amount of +8%. Note that this amount was chosen to reflect realistic changes that could be anticipated over the next years due to global warming conditions; i.e., for WT an +8% increase corresponds to 1-2 deg. C in accordance with relevant global warning studies for the Eastern Mediterranean Sea (Skliris et al., 2007; Skliris et al., 2011). The results of the sensitivity analysis are graphically portrayed in Figure 3. As shown on the figure, an increase of the DO parameter by +8% would lead to a small decrease by -3% on Chl-*a* levels. The increase of pH would cause the Chl-*a* values to increase by approximately 7.9%. A relatively small perturbation of the WT parameter could have a huge impact on algal production, by increasing the Chl-*a* value by 123%. The calculated impact of EC and salinity parameters on algal production is relatively small, by 1.73% and 3.26% respectively. Regarding the nitrogen species, their perturbation effect on the Chl-*a* levels is an increase by 22% for the NH_4^+, 12% for the NO_2^- and 3% for the NO_3^-. Finally, the PO_4^{3-} perturbation would produce an increase of Chl-*a* levels by 10.8%.

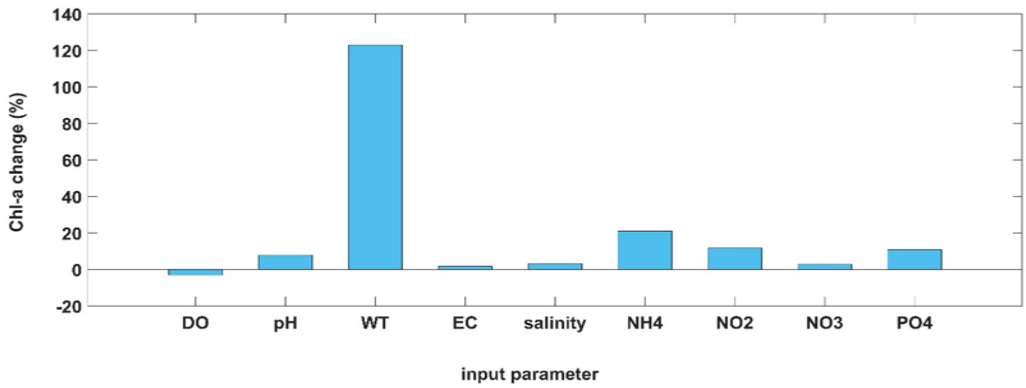

Figure 4. The results of sensitivity analysis, where the input parameters were perturbed by +8% and the associated change in Chl-*a* level is calculated for each of the ANN's input parameter.

4. DISCUSSION

Coastal eutrophication has been identified as one of the most serious environmental issues of the modern world related to nutrients inputs, derived mainly from anthropogenic activities (Maúre et al, 2021). The ecological impacts of eutrophication are catastrophic to the aquatic environment (Gubelit & Berezina, 2010). Besides the ecological impacts, there are also severe economic impacts. As it was estimated by Dodds et al., (2009) the economic cost of eutrophication in the U.S. can reach several billions annually, with the greatest economic losses related with property values and recreational use. Especially for countries that are economically depended on tourism, like Cyprus, the need to maintain good water quality becomes of paramount importance. Cyprus had the highest proportion of excellent water quality for coastal waters (99.3%) among the EU members for the decade 2011-2020 (Jozic et al., 2021), therefore the necessity of management tools for maintaining this excellent water quality is obvious.

ANN modelling studies are very important towards eutrophication control. The created ANNs can be used as management tools against coastal eutrophication (Kuo et al., 2021) and their role can be multi-fold, like prediction of the Chl-*a* levels or early warning against a forthcoming HAB event. The created ANN model successfully simulated the Chl-*a* levels for different sampling points near the Cypriot coastline and based on the provided sensitivity analysis, the impact of the nutrients and the potential WT increase were assessed.

Even though Cyprus trophic status is characterized as ultra-oligotrophic, some sporadic elevated values of Chl-*a* levels have been recorded, which are associated with pollution indices related mainly with anthropogenic activities. As a matter of fact, the waters off the coast of Cyprus, showed some of the lowest Chl-*a* concentrations (10 - 90 ng/l) ever measured in coastal waters (Bianchi et al., 1996). This oligotrophic character of the Eastern Mediterranean and the differences with the Western Mediterranean have been recorded and confirmed many times in the past but also more recently (Crombet et al., 2011). The currently used monitored data are also confirming this, since most of the monitored water bodies are characterized by excellent or good water quality.

The ANN managed to successfully simulate Chl-*a* measurements corresponding to different water quality status. Regarding the data sample no. 673 where Chl-*a* equals with 3.73 (μg/l), it must be noted that even for this unique elevated Chl-*a* value, the ANN simulated it with extremely high accuracy. Additionally, the results of the confusion matrix and the very good classification results regarding the water quality status, are confirming that the created ANN is a reliable predictor. Therefore, the created model can be used not only for forecasting purposes but also for classification of the coastal water quality status of Cyprus.

The sensitivity analysis revealed many interesting behaviours / relationships related to algal production mechanisms near the Cyprus coast. For example, it was found that that the salinity parameter has very small impact on Chl-*a*. According to Espinosa-Carreón et al. (2001), a relationship between salinity increase and Chl-*a* levels increase exists, because high salinity values are related to upwelled subsurface water, which is associated with an increase in nutrient levels. Therefore, the small impact of salinity on the Chl-*a* might be attributed to this indirect relationship.

The water quality of Cyprus is found to be prone to global warming, since based on ANN's calculations, a small increase of the mean WT would cause an enormous increase in Chl-*a* levels by 123%. This means that the mean Chl-*a* levels would be more than doubled. Indeed, it is well established that the increase of WT is strongly associated with an increase in Chl-*a* levels (Rabalais et al., 2009). The WT parameter is considered by Trombetta et al. (2019) as a key factor regulating the marine algal production dynamics and the driving force for HAB events. The role of WT as the most influential parameter as calculated by the ANN, is also verified by the study of Paerl (1996), where it is stated that the production of coastal Chl-*a* is controlled by physical factors (like WT) rather than nutrients.

The EC parameter has a very small impact on Chl-*a* production based on the sensitivity analysis results. Generally, elevated values of EC are correlated with an increase of nutrient levels into the water column (Hadjisolomou et al., 2016). Similarly, with the sensitivity analysis results regarding the salinity parameter, this small impact of EC to the Chl-*a* simulated parameter might be also attributed to this indirect relationship.

The sensitivity analysis found that a small increase in DO levels is related with a decrease in algal production, therefore the DO parameter is negatively related to the Chl-*a* parameter. This finding indicates that while the Chl-*a* level drops, the water becomes less anoxic. This result shows the reverse relationship between Chl-*a* and the DO levels. Therefore, this ANN's finding suggests the interaction between the phenomenon of water column hypoxia and the phenomenon of eutrophication (Vaquer-Sunyer & Duarte, 2008).

Regarding the sensitivity analysis results associated with the pH parameter, an increase of the pH is associated with a small increase of the simulated Chl-*a* levels. This ANN finding can be justified based on the study of Ferreira et al, (2011), stating that there is an association between slightly more alkaline conditions and marine eutrophication.

The nitrogen species (NH_4^+, NO_2^-, NO_3^-) are also impacting the algal production. The Chl-*a* levels are increased with a small increase of nitrogen. Though the mechanism associating the algal production with the nitrogen species is complex and seasonally dependent, it has recently been reported that increased nitrogen levels are related to increased Chl-*a* levels (Vigouroux et al., 2021).

The phosphorus parameter (PO_4^{3-}) is clearly enforcing the algal production mechanism based on the sensitivity analysis results. It has been observed that phosphorus inputs into coastal waters are increasing Chl-*a* production and are related to cultural eutrophication (Rabalais et al., 2009; Paerl et al., 2014). Regarding the Eastern Mediterranean area, it is considered to be a phosphorous limited system (Krom et al., 2004). However, a phosphorus addition experiment in the Eastern Mediterranean has indicated that the nutrient is quickly up-taken through the microbial loop, resulting in a significant increase in Chl-*a* (Krom et al., 2005).

Sensitivity analysis also revealed that the coastal Chl-*a* production mechanism is more impacted by the nitrogen than the phosphorus parameter. This ANN's finding is verified by the observations of Ryther & Dunstan, (1971), stating that the nitrogen is the critical limiting factor to the coastal Chl-*a* production as it was shown by relevant bioassay experiments. This ANN's finding is also confirmed by Vigouroux et al. (2021), noting that the nitrogen is the primary factor related with eutrophication in less-isolated coastal waters. However, for successfully reducing marine coastal eutrophication, both nitrogen and phosphorus parameters must be controlled as it is emphasized by Howarth & Paerl (2008).

5. CONCLUSIONS

Coastal eutrophication is a major environmental issue related not only to human activities, but also to climate change. This ANN modelling study could act as a valuable management tool, which would help water quality managing entities and the associated authorities to maintain the good water quality of Cyprus, since the ANN can be used for prediction but also for classification purposes of the water quality. Considering the ANN's good generalization ability, even for extreme / elevated Chl-*a* values, several management scenarios could be examined. The sensitivity analysis results revealed that the global warming is greatly affecting the coastal algal production. Also, as expected, the increases of nutrients (both nitrogen and phosphorus), are also negatively impacting (but in a lesser extent than WT) the water quality and are promoting cultural eutrophication.

The developed ANN model constitutes a good predictor for the Chl-*a* levels of the Cypriot coastal waters. The model not only managed to predict with very high accuracy Chl-*a* values corresponding to different trophic levels, but also managed to capture the environmental mechanisms related with algal production. The role of the sensitivity analysis was crucial for achieving this, since based on the environmental parameters perturbations their impact could be evaluated. In the future, we plan to use the developed ANN for management purposes for the investigation of possible modelling scenarios. Towards this end, the current ANN will be enhanced and recalibrated with denser measurements coming from other available sources (e.g., satellite data), as well as additional variables (e.g., rainfall, sand-storms), so as to become a powerful management tool.

6. ACKNOWLEDGEMENTS

This work was co-funded by the European Regional Development Fund and the Republic of Cyprus through the Research and Innovation Foundation (STEAM Project: INTEGRATED/0916/0063 and MARI-Sense Project: INTEGRATED/0918/0032).

7. REFERENCES

Antoniadis, K., Rousou, M., Markou, M. et al. (2020). Review-update report of the coastal waters in accordance with Article 5 of the Water Framework Directive (WFD) 2000/60/EC for the period 2013-2019. Department of Fisheries and Marine Research, Ministry of Agriculture, Rural Development and the Environment, Cyprus [In Greek]. Retrieved from: http://www.moa.gov.cy/moa/dfmr/

Bianchi, T.S., A. Demetropoulos, M. Hadjichristophorou, M. Argyrou, M. Baskaran and C. Lambert (1996). Plant Pigments as Biomarkers of Organic Matter Sources in Sediments and Coastal Waters of Cyprus (eastern Mediterranean). *Estuar. Coast. Shelf Sci.*, 42,103-115.

Chang, F.J., Tsai, Y.-H., Chen, P.A., Coynel, A. and Vachaud, G. (2015). Modeling water quality in an urban river using hydrological factors—Data driven approaches. *J. Environ. Manag*., 151, 87–96.

Crombet, Y., Leblanc, K., Queguiner, B., Moutin, T., Rimmelin, P., Ras, J., Claustre, H., Leblond, N., Oriol, L. and Pujo-Pay, M. (2011) Deep silicon maxima in the stratified oligotrophic Mediterranean Sea. *Biogeosciences*, 8, 459-475.

Dedecker, A.P., Goethals, P.L.M., Gabriels, W and De Pauw, N. (2004). Optimization of Artificial Neural Network (ANN) model design for prediction of macroinvertebrates in the Zwalm river basin (Flanders, Belgium). *Ecol. Model.,* 174, 161–173.

Deng, T., Chau, K.-W. and Duan, H.-F. (2021). Machine learning based marine water quality prediction for coastal hydro-environment management. *J. Environ. Manag*., 284, 112051.

Dodds, W.K., Bouska, W.W., Eitzmann, J.L., Pilger, T.J. and Pitts, K.L. (2009). Eutrophication of U.S. freshwaters: Analysis of potential economic damages. *Environ. Sci. Technol*., 43, 12–19.

Elser, J.J., Bracken, M.E.S., Cleland, E.E., Gruner, D.S., Stanley, W., Harpole, W.S. et al. (2007). Global analysis of nitrogen and phosphorus limitation of primary producers in freshwater, marine and terrestrial ecosystems. *Ecol. Lett.,* 10,1135-1142

Espinosa-Carreón, T., Gaxiola-Castro, G., Robles-Pacheco, J. and Nájera-Martínez, S. (2001). Temperature, salinity, nutrients and chlorophyll-a in coastal waters of the Southern California Bight. *Cienc Mar.*, 27, 397–422. https://doi.org/10.7773/cm.v27i3.490

Ferrante, M., Oliveri Conti, G., Fiore, M. and Rapisarda, V. (2013) Harmful algal blooms in the Mediterranean Sea: Effects on human health. *Euromediterr. Biomed*. J., 8, 25–34

Ferreira, J.G., Andersen, J.H., Borja, A. et al. (2011). Overview of eutrophication indicators to assess environmental status within the European Marine Strategy Framework Directive. *Estuar. Coast. Shelf Sci.*, 93,117-131, https://doi.org/10.1016/j.ecss.2011.03.014.

Gebler, D., Kolada, A., Pasztaleniec, A. and Szoszkiewicz, K. (2020). Modelling of ecological status of Polish lakes using deep learning techniques. *Environ. Sci. Pollut. Res*., 28, 5383–5397

Goethals, P.L.M, Dedecker, A.P., Gabriels, W., Lek, S. and De Pauw, N. (2007). Applications of artificial neural networks predicting macroinvertebrates in freshwaters. *Aquat. Ecol*., 41, 491-508.

Gubelit, Y.I. and Berezina, N.A. (2010). The causes and consequences of algal blooms: The Cladophora glomerata bloom and the Neva estuary (Eastern Baltic Sea). *Mar. Pollut. Bull*., 61, 183–188.

Guo, J., Ma,Y. and Lee, J.H.W. (2021). Real-time automated identification of algal bloom species for fisheries management in subtropical coastal waters. *J. Hydro-Environ. Res*., 36,1-32, https://doi.org/10.1016/j.jher.2021.03.002.

Hadjisolomou, E., Stefanidis, K., Papatheodorou, G. and Papastergiadou, E. (2016). Assessing the contribution of the environmental parameters to eutrophication with the use of the “PaD” and “PaD2” methods in a hypereutrophic lake. *Int. J. Environ. Res. Public Health*, 13, 764, https://doi.org/10.3390/ijerph13080764

Hadjisolomou, E., Stefanidis, K., Papatheodorou, G. and Papastergiadou, E. (2018) Assessment of the eutrophication-related environmental parameters in two Mediterranean lakes by integrating statistical techniques and self-organizing maps. *Int. J. Environ. Res. Public Health*,15, 547, https://doi.org/10.3390/ijerph15030547

Hadjisolomou E, Stefanidis K, Herodotou H, Michaelides M, Papatheodorou G, Papastergiadou E. (2021). Modelling Freshwater Eutrophication with Limited Limnological Data Using Artificial Neural Networks. *Water*, 13, 1590, https://doi.org/10.3390/w13111590

Han, H.-G., Qiao, J.-F. and Chen, Q.-L. (2012). Model predictive control of dissolved oxygen concentration based on self-organizing RBF neural network. *Control. Eng. Pract*., 20, 465-476.

Howarth, R. and Paerl, H.W. (2008). Coastal marine eutrophication: Control of both nitrogen and phosphorus is necessary. Proceedings of the National Academy of Sciences Dec, 105 (49) E103; DOI: 10.1073/pnas.0807266106

Krom, M. D., Herut, B. and Mantoura, R. F. C. (2004). Nutrient budget for the Eastern Mediterranean: Implications for phosphorus limitation. *Limnol Oceanogr*, 49, 1582-1592.

Krom, M. D., Thingstad, T.F., Brenner,S. et al. (2005). Summary and overview of the CYCLOPS P addition Lagrangian experiment in the Eastern Mediterranean. *DEEP-SEA RES PT II*, 52, 3090–3108, doi:10.1016/j.dsr2.2005.08.018

Lee, J.H.W., Huang, Y., Dickman, M. and Jayawardena, A.W. (2003). Neural networking modelling of coastal algal blooms. *Ecol. Model*., 159, 179-201

Lee, S., Park, I., Koo, B.J., Ryu, J.-H., Choi, J.-K. and Woo, H.J. (2013). Macrobenthos habitat potential mapping using GIS-based artificial neural network models. *Mar. Pollut. Bull*., 67, 177-186.

Li, P., Hua, P., Gui, D. et al. (2020). A comparative analysis of artificial neural networks and wavelet hybrid approaches to long-term toxic heavy metal prediction. *Sci. Rep*., 10, 13439 https://doi.org/10.1038/s41598-020-70438-8

Maier, H.R. and Dandy, G.C. (2000). Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. *Environ Model Softw*., 15, 101-124.

Maúre, E.d.R., Terauchi, G., Ishizaka, J. et al. (2021). Globally consistent assessment of coastal eutrophication. *Nat Commun*, 12, 6142. https://doi.org/10.1038/s41467-021-26391-9

Mishra, M., Naik, S., Babu,V.P., Pradhan, U. et al. (2021). Algal bloom, hypoxia, and mass fish kill events in the backwaters of Puducherry, Southeast coast of India. Oceanologia, https://doi.org/10.1016/j.oceano.2021.11.003

Muttil, N. and Chau, K.-W. (2007). Machine-Learning Paradigms for Selecting Ecologically Significant Input Variables. Engineering Applications of Artificial Intelligence, 20 (6). pp. 735-744. ISSN 0952-1976

Olden, J., Lawler, J. and Poff, N.L. (2008). Machine Learning Methods Without Tears: A Primer for Ecologists. *Q. Rev. Biol*., 83, 171–193.

Ozić, S., Baljak, V., Cenov, A., Lušić, D. et al. (2021). Inland and Coastal Bathing Water Quality in the Last Decade (2011–2020): Croatia vs. Region vs. EU. *Water*, 13, 2440. https://doi.org/10.3390/w13172440

Paerl, H.W. (1996) A comparison of cyanobacterial bloom dynamics in freshwater, estuarine and marine environments. *Phycologia*, 35, 25-35.

Paerl, H.W., Hall, N.S., Peierls, B.L. et al. (2014). Evolving Paradigms and Challenges in Estuarine and Coastal Eutrophication Dynamics in a Culturally and Climatically Stressed World. *ESTUAR COAST*, 37, 243–258.

Pule, M., Yahya, A. and Chuma, J. (2017). Wireless sensor networks: A survey on monitoring water quality. *J. Appl. Res. Technol.*,15, 562-570, https://doi.org/10.1016/j.jart.2017.07.004.

Rabalais, N.,Turner, E., Diaz, R. and Justic, D. (2009). Global change and eutrophication of coastal waters. *ICES J. Mar. Sci.*, 66,1528–1537, https://doi.org/10.1093/icesjms/fsp047

Ram, A., Jaiswar, J.R.M., Rokade, M.A., Bharti, S., Vishwasrao, C. and Majithiya, D. (2014). Nutrients, hypoxia and mass fish kill events in Tapi Estuary, India. *Estuar. Coast. Shelf Sci*., 148, 48-58.

Ryther, J. H. and Dunstan, W. M. (1971). Nitrogen, Phosphorus, and Eutrophication in the Coastal Marine Environment. *Science*, 171,1008–1013. http://www.jstor.org/stable/1731314

Salami Shahid, E. and Ehteshami, M. (2016). Application of artificial neural networks to estimating DO and salinity in San Joaquin River basin. *Desalin. Water Treat*., 57, 4888-4897.

Sarkar, A. and Pandey, P. (2015). River Water Quality Modelling using Artificial Neural Network Technique. *AQUAT PR*, 4, 1070-1077.

Scardi, M. and Harding, L.W., Jr. (1999). Developing an empirical model of phytoplankton primary production: A neural network case study. *Ecol. Modell*., 120, 213–223.

Skliris, N., Sofianos, S. and Lascaratos., A. (2007). Hydrological changes in the Mediterranean Sea in relation to changes in the freshwater budget: A numerical modelling study. *J. Mar. Syst*., 65, 400–416, doi:10.1016/j.jmarsys.2006.01.015

Skliris, N., Sofianos, S., Gkanasos, T. et al. (2011). Long-term sea surface temperature variability in the Aegean Sea. *Adv. Oceanogr. Limnol.*, 2, 125-139.

Sliskovic, M., Jelic-Mrcelic, G., Antolic, B. et al. (2011). The fouling of fish farm cage nets as bioindicator of aquaculture pollution in the Adriatic Sea (Croatia). *Environ Monit Assess* 173, 519–532, https://doi.org/10.1007/s10661-010-1402-y

Trombetta, T., Vidussi, F., Mas, S., Parin, D., Simier, M. and Mostajir, B. (2019). Water temperature drives phytoplankton blooms in coastal waters. *PLoS ONE* 14(4): e0214933. https://doi.org/10.1371/journal.pone.0214933

Tselepides, A., Papadopoulou, N., Podaras, D., Plaiti, W. and Koutsoubas, D. (2000). Macrobenthic community structure over the continental margin of Crete (South Aegean Sea NE Mediterranean). *Prog. Oceanogr.*, 46, 401–428

Vaquer-Sunyer, R. and Duarte., C.M. (2008). Thresholds of hypoxia for marine biodiversity. *Proc. Natl. Acad. Sci. U. S. A*.,105, 15452-15457, DOI: 10.1073/pnas.0803833105

Vigouroux, G., Kari, E., Beltrán-Abaunza, J.M., Uotila, P., Yuan, D. and Destouni, G. (2021). Trend correlations for coastal eutrophication and its main local and whole-sea drivers – Application to the Baltic Sea. *Sci. Total Environ*., 779,146367, https://doi.org/10.1016/j.scitotenv.2021.146367.