Dissolved oxygen estimation in aquaculture sites using remote sensing and machine learning

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ABSTRACT

Dissolved oxygen (DO) is one of the most critical parameters for aquaculture, as it is vital for all living organisms. The survival, growth and food intake of fish is directly affected by changes in DO concentration. Therefore, the systematic and continuous monitoring of DO is of crucial importance for proper production management. DO does not change the optical properties of water, so it is impossible to estimate its concentration directly from the reflection values of satellite sensors. However, several studies have suggested that it can be estimated indirectly, based on its correlation with other parameters such as chlorophyll-a (chl-a) and sea surface temperature (SST). The present study aims to integrate satellite data, along with *in-situ* observations to bring forth innovative approaches on how DO can be estimated and monitored on large scale near aquaculture facilities. In this context we exploited daily CMEMS data (chl-a and SST) along with *in-situ* data (DO) to train a support vector regression (SVR) model. Our *in-situ* dataset included daily DO measures from Agrilia fish farm in Lesvos for the year 2021. The accuracy of our model was tested us- ing the value of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Our preliminary results indicate that our model performs well locally with promising scalability, which paves the way for the development of real-time monitoring systems for aquaculture.

Introduction

Oxygen is, along with temperature, one of the most critical environmental parameters affecting the physiology and performance of marine organisms since it is requisite for aerobic metabolism. Consequently, the concentration of dissolved oxygen (DO) in the water is a monitoring parameter of great importance for finfish aquaculture as it directly affects the survival, growth, food intake, and health of the farmed fish (Oldham et al., 2019), (Burt et al., 2012). For an aquaculture cage in particular, the systematic and continuous monitoring of DO constitutes a necessity because the environmental conditions at the rearing sites are outside human control (as opposed to land-based production systems) and are therefore prone to fluctuations that may threaten production.

Traditionally, DO has been monitored with in-situ measurements using sensors either manually or, more recently, with semi- automated and automated systems (Parra et al., 2018). While such modes of DO monitoring are simple and have been effective for the empirically-driven practices of the past, the rapid expansion of aquaculture towards precise, data-driven management (precision farming) necessitates the development and implementation of advanced systems that utilize automation and modern technologies to- wards forecasting and real-time monitoring (O'Donncha and Grant, 2020), (Raju and Varma, 2017). Of particular importance is the possibility of forecasting the oxygen concentration in the farm depending on the site-specific characteristics of the farming area and its surroundings. For this information, *in situ* sensors are not particularly efficient as they cannot provide the required area coverage. Furthermore, organized zones of aquaculture activity with several farms installed have similar needs and, large scale monitoring is essential for forecasting. A promising field that may provide useful tools in that context is remote sensing.

Remote sensing is widely used for the detection of optically active parameters such as chlorophyll-a (chl-a), total suspended matter, and temperature. Satellite sensors are able to detect parameters that affect the optical properties of water at specific wavelengths (e.g. chl-a). Therefore, it is unlikely to record the concentration of DO directly from the reflection values of the satellite sensors. However, research has shown that it can be estimated indirectly because of its correlation with other parameters, such as temperature and chl-a (Guo et al., 2021), (Kim et al., 2020).

DO generally exhibits a negative correlation with sea temperature (Matear and Hirst, 2003). As the temperature of water increases, the solubility of oxygen decreases. Therefore, seasonal variations of DO concentration can be observed in surface waters in winter and early spring when there is a peak and, in the summer, where the concentration reaches the lowest point. Especially in the Mediterranean studies have shown that solubility due to temperature is the main driving force of DO concentrations in surface waters (Mavropoulou et al., 2020).

Another major oceanographic parameter that greatly affects the levels of DO is the primary production. In remote sensing, primary production is usually quantified by chl-a concentration that acts as an index of phytoplankton abundance in surface waters (Guy et al., 1993), (Lewis et al., 2016). In the daytime, due to photosynthesis, phytoplankton releases oxygen and as such, there is a positive correlation between chlorophyll concentration and DO. This is particularly evident in the productive water layer, the depth of which varies between the surface and the thermocline and between seasons and phytoplankton species. Oxygen levels are higher in surface waters because that is where the ocean-atmosphere gas exchange occurs and lower at depths below 200m because that is where the euphotic zone generally ends and oxygen absorption due to organic matter decomposition starts. On the other hand, research has shown that high concentrations of phytoplankton can have a reverse effect (Wang et al., 2019). During night-time, when there is an absence of light, phytoplankton absorbs oxygen and, in case of high abundance, it can even cause anoxic conditions in the water. In these cases, the surrounding environment deteriorates with a negative impact on larger organisms, such as fish. In the case of aquaculture farms where fish are in high concentrations the impact may be worse.

Knowing the above theoretical mechanisms, several researchers have tried to develop models based on the correlation of DO with several environmental parameters, such as sea surface temperature (SST) and chl-a, to estimate its concentration and distribution.

Karakaya and Evrendilek (2011) developed multiple regression models to estimate water parameters (turbidity, DO, nitrite nitrogen, silicate, biological oxygen demand, chl-a) using Landsat 7 (ETM+) data. They used 18 Landsat 7 images and field measurements from 16 stations on approximately same dates. Their results were very promising ($R^2 = 0.81$), however, the developed methodology is based on local measurements and cannot be generalized in other study areas.

Another interesting approach published by Batur's and Maktav's (Batur and Maktav, 2019), attempts to combine machine learning and regression techniques (Response Surface Regression -RSR, Multiple Linear Regression - MLR, Artificial Neural Network - ANN, Support Vector Machines - SVM), using satellite data (Landsat-8, Sentinel-2, Goturk 2) and field measures for the estimation of DO. Their results indicated that RSR performed better than the other three methods (MLR, ANN, SVM) with R^2 equal to 0.89.

The methods mentioned perform well locally but are difficult to generalize. In this context, Kim et al. (2020) tried to overcome this challenge by correlating DO with parameters that can be directly measured from satellite sensors (SST, chl-a) using multiple regression (MLR) to create a linear relation between the parameters. Pearson correlation analysis showed that DO is highly correlated with SST and chl-a. Stepwise multiple regression was then used to develop a linear relation among DO, SST and chl-a. The proposed model was then applied to MODIS and VIIRS products to observe the spatial and temporal changes in DO in the Saemangeum offshore areas, Yellow Sea. The results showed a strong correlation between measured and predicted values of DO ($R^2 = 0.801$) and the study showed the potential for monitoring DO from satellite sensors.

Similarly, Guo et al. (2021) developed a generalized approach for the estimation of DO, based on Support Vector Regression (SVR). Besides estimating DO and comparing several different methods, they also investigated the correlation of DO with other para- meters (air temperature, incident shortwave radiation flux density, precipitation, nutrients). They exploited Landsat images for years 2000–2018 and daily MODIS data. From the comparison among the four different kernels (linear, polynomial, sigmoid, radial basis) radial basis function (RBF) performed best. They also compared SVR to random forest (RF) and multiple regression (MLR), and according to their results SVR outperformed the other two methods.

So far literature has highlighted the contribution of remote sensing and machine learning in the estimation of DO; however, the challenges of coastal zones and aquaculture processes have not been addressed yet. While previous research has been successful in estimating DO in the water, the sparsity of data, the spatial resolution, and the scope of the existing studies does not fully account for the importance of daily and reliable data for meeting aquaculture needs at the coastal zone. In this context, the purpose of our study was to develop a methodology for the estimation of DO in coastal areas with aquaculture facilities, based on daily CMEMS data and machine learning techniques.

Methods and data

Study site

The test site is located at the South-Eastern part of Lesvos Island (Agrilia), in North Aegean Sea (Fig. 1). The North Aegean is chaacterized by lower salinity values (37–39 psμ) than the South Aegean (>38.5 psμ) (Zervakis and Georgopoulos, 2002) due to the Dardanelles Strait which inputs low salinity flow of water to the plateau of Lemnos. At the same time, studies have shown that the fresh waters of the strait directly affect the seasonal circulation patterns due to the buoyancy of the water in Aegean (Androulidakis and Kourafalou, 2011). North Aegean is generally characterized as an oligotrophic sea, due to a lack of phosphorus (Krom et al., 1991). The capacity of the farm in the studied area is 380T per year and the main fish farmed are the European sea bass (*Dicentrarchus labrax*) and the gilthead sea bream (*Sparus aurata*). The unit consists of circular cages of 10m–20 mm diameter. Water temperature in the surrounding area ranges between 14 °C to 24 °C and the salinity is constant at 39 psμ. The average depth in the farming area is approximately 50m.

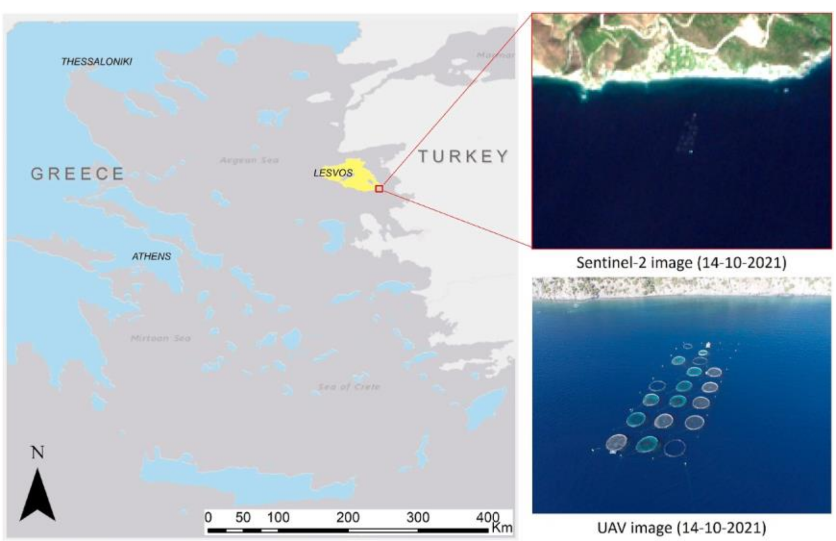

Fig. 1. The study site is located at the South-Eastern part of Lesvos Island (Agrilia).

Satellite data

Most recent satellite sensors offer a wide range of data products useful for estimating water quality parameters at large scale temporally. However, they are not suitable to be adopted as a standalone solution in real case scenarios due to their inability to collect data under heavy cloud coverage.

Copernicus Marine Environment Monitoring Service (CMEMS)[1] provides regular and systematic biogeochemical and physical in- formation on the marine. In the framework of our study, we exploited Level-4, daily, gap-free satellite observations for chl-a concentration and SST from multi-platform observations. We use CMEMS data to describe environmental conditions and study their correlation to the concentration of DO. Knowing this relation, in-situ observations of DO are used to train a machine learning regression model.

In-situ data

Our *in-situ* dataset includes field measures of DO and SST from Agrilia fish farm in Lesvos, collected for the year 2021. DO is measured daily (8:00am - 10:00am) using Oxy Guard scavenging packet. The 80% of the dataset was used as training sample and the remaining 20% was used as test sample.

Methodology

Regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Regression methods are used to estimate the relation between a dependent variable and one or more independent variables (features). In this study our aim is to estimate the concentration of DO in relation to chl-a and SST. All the parameters are described in continuous values, so we selected the implementation of a regression model instead of classification. Commonly used regression models include Simple Linear Regression, Polynomial Regression and Logistic Regression. For the present study, we developed an approach for DO estimation based on a Support Vector Regression machine learning model, using CMEMS data and in-situ observations. For every set of coordinates an array was created including the values of chl-a and SST, as well as the values of one, two and three days prior to the sampling.

Support Vector Regression (SVR) uses the same principles as SVMs but returns continuous values instead of classified. SVR has been proven to be successful in solving linear and nonlinear problems and perform sufficiently with limited datasets (Guo et al., 2021). Support Vector Machines is a nonlinear and non-parametric large margin supervised machine learning classifier implementing Vapnik's structural risk minimization principle (Vapnik, 1995). Most linear regression methods are based on the minimization of the sum of squared errors. In SVR the objective is to handle the error in constraints, giving the flexibility to choose our tolerance, find the appropriate hyperplane and define the acceptable error margins (ε). Essentially, the hyperplane is the decision surface that describes the optimal values. Altering the maximum ε allows to achieve the desired accuracy to our model. The slack variables ξ allow some training errors, guaranteeing robustness to noise and outliers. The objective function and the constraints are described by the following equations (1) and (2):

$$MIN\frac{1}{2}\,\|w\|\,2 + \mathrm{C}\sum_{i=1}^{n}|\xi| \tag{1}$$

$$|y_i - w_i x_i| \leq \varepsilon + |\xi| \tag{2}$$

where y_i is the target, w_i is the coefficient, and x_i is the predictor (feature). C corresponds to a user selected parameter to control the complexity of the model, acting as a trade-off parameter between nonlinearity and number of training errors.

[1] https://marine.copernicus.eu/

To represent more complex hyperplane shapes than the linear methods, the techniques can be extended by using kernel functions (Chatziantoniou et al., 2017). The most common kernels include polynomial kernel, radial basis function (RBF), and sigmoid kernel. In this study, RBF kernel was used due to its promising capabilities (Guo et al., 2021).

SVR is simple structured and supported by several programming languages. For the implementation of the model in our study we used the scikit-learn library (v.0.18.1) in Python 3.4. The evaluation of the model was conducted using the residuals and two statistical indices, namely, mean absolute error (MAE), root mean squared error (RMSE). MAE calculates the precision expressing the average distance between the estimated and the real values, and is described by equation (3). RMSE describes the standard deviation of the residuals (equation (4)).

$$MAE + \sum_{i=1}^{n} \frac{|y_i - x|}{n} \tag{3}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - x_i)^2}{n}} \tag{4}$$

where y_i is the predicted values and x_i the measured values.

Additionally, in order to evaluate the fitness of our model, R^2 was also calculated. R^2 is widely used in remote sensing classification studies, however it is not recommended for evaluating regression models as it only expresses how well the regression line approximates the real data point without considering all parameters.

The initial dataset included four columns (dates, DO *in-situ*, latitude and longitude). Using the dates and the coordinates as primary key another 8 columns were added with the values of chl-a and SST from CMEMS for each date and the previous 3 days (chl, chl_{d-1}, chl_{d-2}, chl_{d-3}, sst, sst_{d-1}, sst_{d-2}, sst_{d-3}). After removing the empty entries, the dataset was divided in training and testing sample (80%–20%). The results were used to calculate the Mean Absolute Error (MAE) and produce the residuals' plots, correlation chart and time series. In Fig. 2 a graphical representation of the approach is presented.

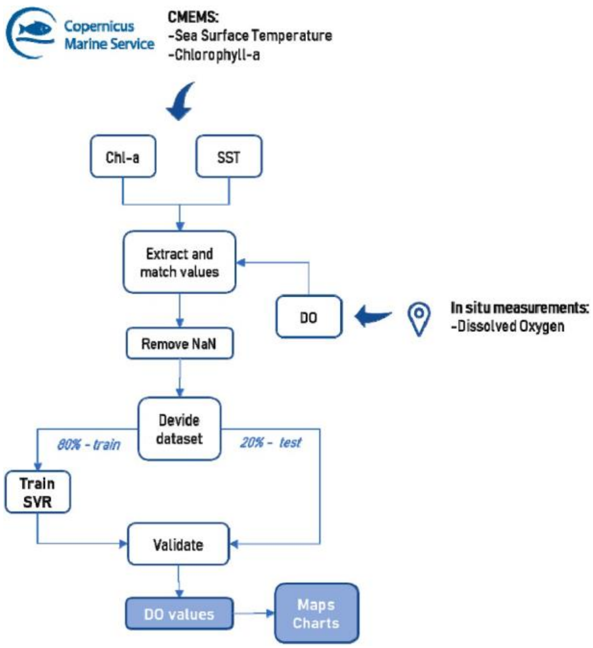

Fig. 2. Flowchart of the implemented methodology.

1. Results

1.1. *Temporal and spatial variability*

The data collected from CMEMS (chl-a, SST) and the estimated DO were used to create daily maps for examining the spatial distribution of the aforementioned parameters. The maps represent the concentration of chl-a, sst and DO in the surrounding area with spatial resolution of 1 km.
The following maps present the prevailing conditions of SST, chl-a (Fig. 3, Fig. 4) and DO (Fig. 4) in the surrounding sea area of Lesvos for 12/03/2022. SST ranges between 14 °C - 16 °C and exhibit the lowest values near the north-east part of the island (14 °C), while they gradually ascend towards the south-western part (up to 16 °C). This gradient is related to the upwelling processes near the coastal region of western Lesvos, affecting the water circulation of the area (Androulidakis et al., 2017). A similar inverse pattern is observed in the concentration of chl-a, however the values range between 0.2 and 1 mg m^{-3}. Higher values are observed in the north- eastern part of the island, near the coastline and inside the gulf of Gera. Overall, the concentration does not exceed 0.6–0.7 mg m^{-3} across the whole studied area.
The concentration of DO was estimated in relation to SST and chl-a. Consequently, the spatial distribution as presented in Fig. 5 follows the same pattern. Higher concentration is observed in the north-eastern waters, near the coastline and within the gulf of Gera, presenting an obvious negative correlation with SST and a weaker positive correlation with chl-a.
Examining the time series of the SVR results, no significant seasonal variability was detected. The DO concentration varied from 7 to 7.8 ppm across the year with four major drops below 6.5 ppm. Highest values were detected in the winter and spring months and the lowest during summer and fall. The highest values were detected in the winter and spring months and the lowest during summer and fall. According to Souvermezoglou et al. (2014)), North Aegean surface layers are highly influenced by the influx waters of the Black Sea through the Dardanelles Strait. These waters, compared to the Aegean, are rich in nutrients but have a high seasonal variability (Krom et al., 1991).

Specifically, in winter and spring phosphate concentrations can be more than doubled in relation to autumn. These nutrients are directly correlated to phytoplankton abundance which again is one of the main driving forces of oxygen generation and release in the surface water layers.

In relation to the in-situ measurements, the DO seasonal variability can be tracked through both SST and chl-a (Fig. 6). This is especially true from January through September, when the negative correlation with SST and the positive with chl-a is clearly high- lighted. In winter, lower temperatures in combination with high phytoplankton concentration allows bigger oxygen production with a higher level of retention form the water column. On the other hand, in the summer the reduction of the inflow of inland waters limits the nutrient concentration in the water column with a direct impact on phytoplankton abundance. Furthermore, the heated surface has a limited capacity for oxygen retention. According to these results it would be expected that in the fall, when the temperatures start to drop and chl-a concentration rises, the DO would also rise, but this behaviour is not present. Instead, the DO levels remain similar to those in the summer months.

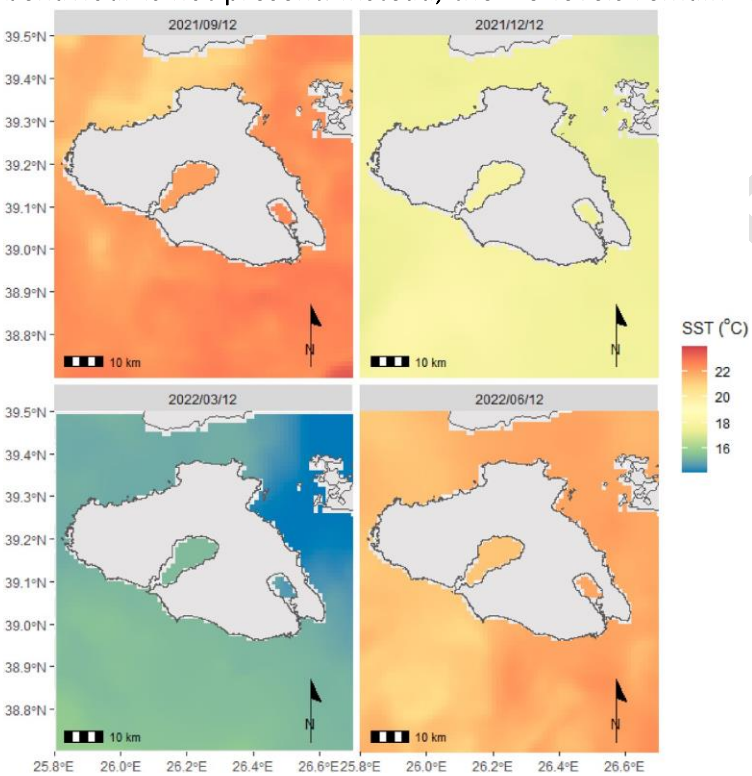

Fig. 3. The spatial distribution of SST around Lesvos Island for four representative dates (fall, winter, spring, summer).

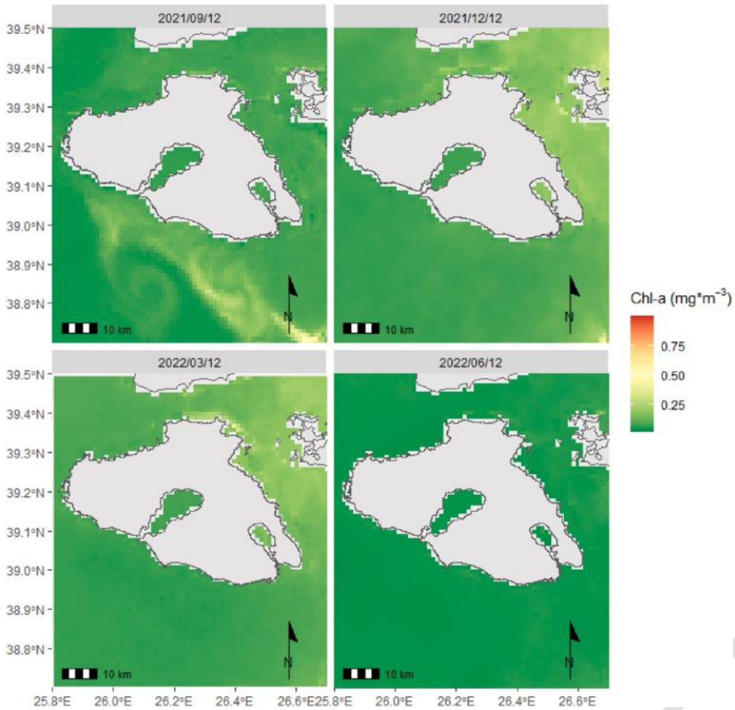

Fig. 4. The spatial distribution of CHL-a around Lesvos Island for four representative dates (fall, winter, spring, summer).

DO presented weak correlation with both chl-a and SST. DO and chl-a had a positive trend on the scale of 0.17 and DO and SST a stronger negative correlation of −0.39 (Table 1). These results are in agreement with the theoretical mechanisms of DO concentration in water as cooler waters can retain more oxygen molecules compared to warmer and phytoplankton releases oxygen in the water column during the day.

1.2. *Model performance*

The model's accuracy and precision were examined based on the MAE and RMSE indices. The model produced results with a MAE of 0.11 and RMSE of 0.13 (Table 2). The rating stands close the decimal precision of the in-situ measurements which had a decimal precision of one. An error of 0.11 can be considered acceptable for most real-life applications as meaningful fluctuations of DO.

Accuracy can be explored with the residual plot in Fig. 3. The residuals present an even distribution around 0, showcasing high ac- curacy. There is no visible fluctuation around the 0 axis that could hint to a different model response based on the DO levels. Constant variation of residuals means that the rate of error also remains constant on both ends of the value spectrum and that the model has a low variation of resulting errors. Similar conclusions are extracted by the density plot (Fig. 7), where the residuals present a normal distribution around the mean. There is no significant deviation on either side of the histogram that could point to unbalanced results, and the bias is around the value of 0.1, close the MAE results.

2. **Discussion and conclusions**

The present study was aiming at the development of a methodology for the estimation of DO near aquaculture facilities. In this context we exploited daily CMEMS data (chl-a and SST) along with in-situ data (DO) to train an SVR model. The accuracy of our model was tested using the value of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), as well as the residuals' plot. The most common used error metrics for evaluating a regression model are MAE and RMSE. Both metrics are describing the distance between the actual and the predicted values and are measured in the same units as the output variable, making the interpretation of loss easy. Our model performed well with MAE of 0.11 and RMSE of 0.13, and the residuals were evenly distributed around 0. Our results showed high precision and accuracy. We have chosen to use MAE and RMSE indices to validate our model as they give as a clearer view of the error and distribution of the residuals. On the contrary, R^2 was poor (0.32) compared to other studies. For example Guo et al. (2021) reached a score of 0.94 using a similar approach in inland waters for a long term analysis. R^2 is generally used in similar studies to examine the fitness of the model instead of the performance, and it is not representing of the magnitude and direction of error. R^2 creates a baseline model to compare the trained model and is a good measure to determine how well the model fits the dependent variables, however it does not give any information about the distribution of the residuals. For this reason, MAE and RMSE are considered to be more appropriate to validate the performance of regression models as they give information about the closeness of the prediction to the actual values. In this context we do not consider the poor value of R^2 to be overall disappointing for our results.

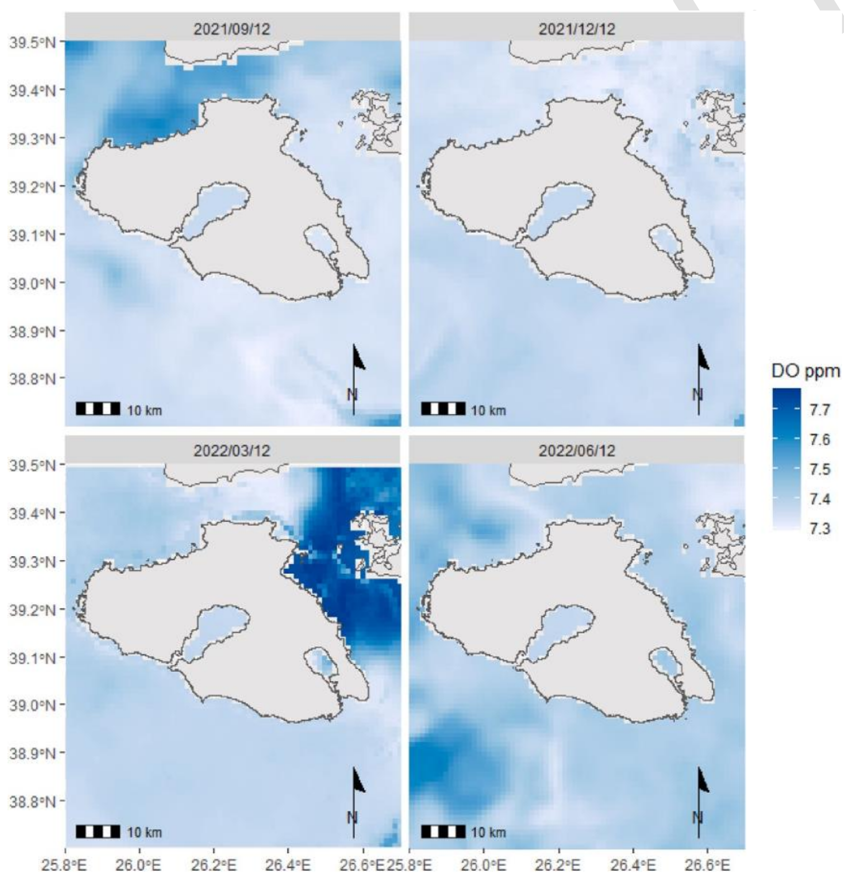

Fig. 5. The spatial distribution of DO around Lesvos Island for four representative dates (fall, winter, spring, summer).

The timeseries analysis highlighted some extreme values during the summer, however they are not considered critical to the farm as the saturation of oxygen is greater than 80%. The values of chl-a and DO present small changes during the year (range <1 unit) and they do not appear to have significant correlation (0.17), but taking into consideration both the temporal and the spatial distribution we can observe a positive trend connecting the two variables. On the contrary, SST ranges from 16 °C to 26 °C and the correlation with both chl-a and DO is stronger but negative (−0.67 and −0.39 respectively). This inverse correlation has also been reported by Kim et al. (2020) who performed a multiple linear regression for a long term analysis with correlation coefficients ranging from −0.743 to −0.792.
The method we chose to use in our study (SVR) has also been used with promising results in the studies of Batur and Maktav (2019) and Guo et al. (2021) and outperformed several other approaches (Linear Regression, Multiple Linear Regression, Random Forests). Guo et al., 2021 ((Guo et al., 2021)) also suggest this method over others based on its low complexity which makes it easy to be adopted by several programming language, and the ability to solve linear and nonlinear problems, even with limited datasets. Both studies also report the promising scalability and generalizability of SVR in comparison to simple and multiple linear regression models.

Our results show a promising approach for estimating DO at aquaculture sites, which paves the way for the development of real- time monitoring systems for aquaculture. The methodology was successful at correlating DO with SST and chl-a, while the precision of the estimates was also high when compared with field data. The method was able to depict not only shifts in the seasonal patterns of DO but also to detect sudden drops in concentration in at least four occasions during the summer (Fig. 6). While the drops in the analyzed time-series are of minor practical interest because they are relatively small and thus, don't constitute a concern for fish health (saturation remained >80%), the capability of the method to realistically capture them is reflective of its potential as a monitoring tool. Abrupt changes in DO typically occur in the summer, as seen here, during heatwaves or low circulation periods leading to hy poxic events. Severe hypoxic events can be detrimental to the fish as they cause increased mortalities and substantial energetic costs related to their stress response (Wade et al., 2019), (Vikeså et al., 2017). Therefore, the usefulness of a monitoring tool for DO is largely associated with its accuracy at capturing theses rare but life-threating, for the fish, events.

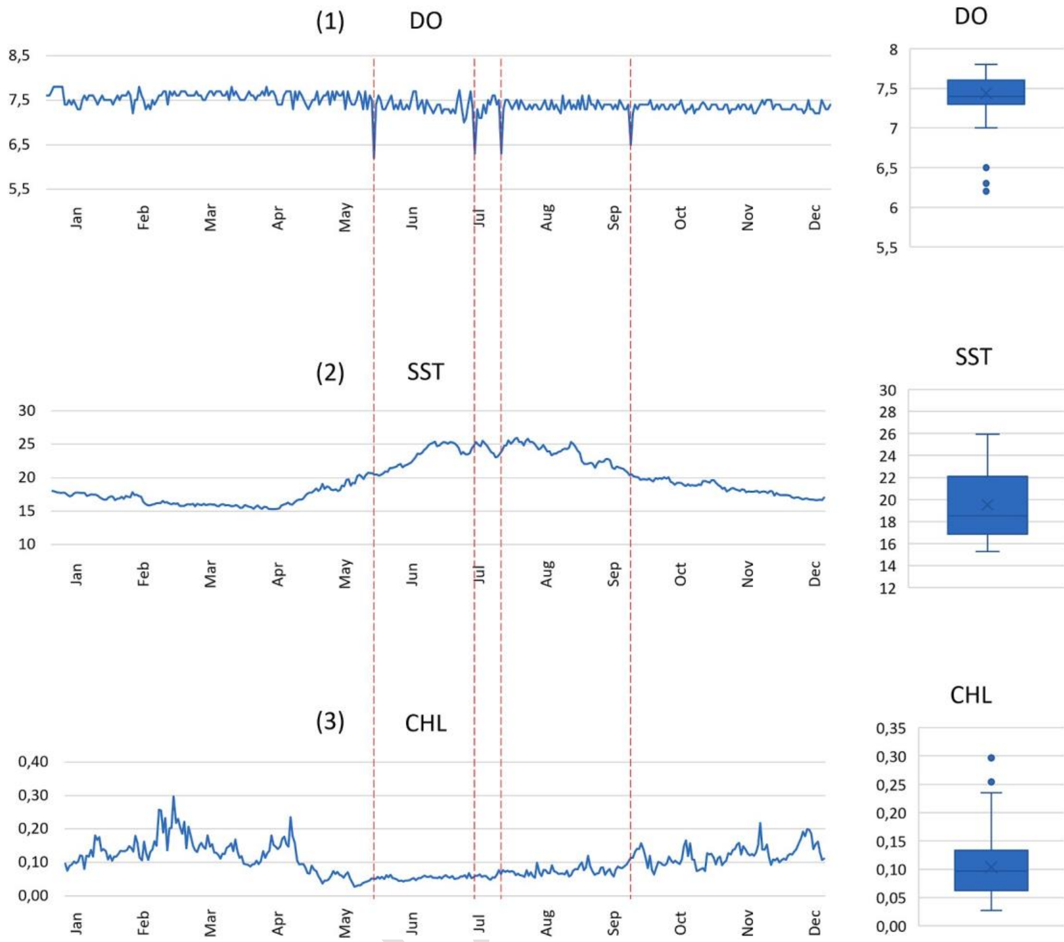

Fig. 6. Seasonal variability of DO (1), SST (2) and chl-a (3), along with the boxplots which show the distribution of their values.

Table 1
Correlation between chl-a, SST and DO.

	SST	DO	CHL
SST	1		
DO	−0,39	1	
CHL	−0,66	0,17	1

Table 2
Model performance results.

MAE	RMSE	R^2
0,11	0,13	0,32

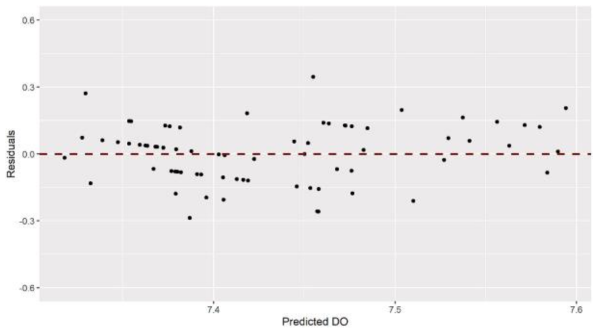

Fig. 7. Density plot presenting the residuals distribution around 0.

Another advantage of using this method for the estimation of DO is that it increases the spatial scale at which monitoring can occur. While *in-situ* sensors are paramount for precise measurements within a single cage of a farm, a remote sensing approach offers a better representation of the oxygen conditions, and thus, potential dangers, at a larger area. Considering that aquaculture farms are often aggregated within the limited coastal space of suitable farming areas, either as single operations or as an organized industrial park, it is imperative for the aquaculture producers to monitor the DO at a higher spatial scale. The same applies to administrative authorities that may be interested in the supervision of zones of organized aquaculture activity at a regional level.
Our preliminary results are promising and indicate correlation between SST, chl-a and DO. The predicted and the measured values differ less than 3% in most cases. The lack of extreme incidents during the study period and the low variability of the values in the area makes the prediction more challenging, since the model is only trained for a limited range of values. This is considered to be a weakness of this study, as we have noticed that when the values exceed the normal range, the differences between the predicted and measured values are higher. In order to overcome this challenge, we are planning to expand our study to more sites with different pre- vailing conditions to feed our model with more data. Increasing the dataset to include more cases is essential for proper training of the model and, consequently, for improving our results

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