Science of the Total Environment 874 (2023) 162599

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

The air temperature change effect on water quality in the Kvarken Archipelago area

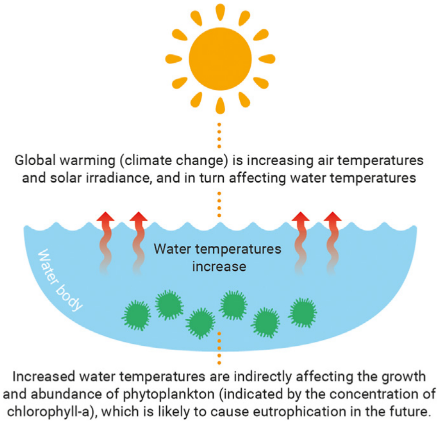
N. Girgibo [a,*], X. Lü [a,b], E. Hiltunen [a], P. Peura [a], Z. Dai [c]

[a] Department of Energy Technology, School of Technology and Innovations, University of Vaasa, P.O.Box 700, FIN-65101 Vaasa, Finland
[b] Department of Civil Engineering, Aalto University, P.O.Box 12100, FIN-02130 Espoo, Finland
[c] College of Construction Engineering, Jilin University, Changchun 130026, China

HIGHLIGHTS

- Climate change increase air, water and chlorophyll-a concentration in a few months.
- Climate change effect is seen in air temperature influencing water temperature.
- Water temperature and other parameters influenced chlorophyll-a concentration.
- An indirect effect of air temperature on chlorophyll-a concentration is shown.
- Understanding what kind of changes can be seen in water systems is important.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Ashantha Goonetilleke

Keywords:
Global warming
Climate
Water quality
Chlorophyll-a
Water and air temperature
Climate change effects

ABSTRACT

The Kvarken Archipelago is Finland's World Heritage site designated by UNESCO. How climate change has affected the Kvaken Archipelago remains unclear. This study was conducted to investigate this issue by analyzing air temperature and water quality in this area. Here we use long-term historical data sets of 61 years from several monitoring stations. Water quality parameters included chlorophyll-a; total phosphorus; total nitrogen; coliform bacteria thermos tolerant; temperature; nitrate as nitrogen; nitrite-nitrate as nitrogen, and Secchi depth and correlations analysis was conducted to identify the most relevant parameters. Based on the correlation analysis of weather data and water quality parameters, air temperature showed a significant correlation with water temperature (Pearson's correlations = 0.89691, $P < 0.0001$). The air temperature increased in April (R^2 (goodness-of-fit) = 0.2109 & $P = 0.0009$) and July ($R^2 = 0.1207$ & $P = 0.0155$) which has indirectly increased the chlorophyll-a level (e.g. in June increasing slope = 0.39101, $R^2 = 0.4685$, $P < 0.0001$) an indicator of phytoplankton growth and abundance in the water systems. The study concludes that there might be indirect effects of the likely increase in air temperature on water quality in the Kvarken Archipelago, in particular causing water temperature and chlorophyll-a concentration to increase at least in some months.

---

* Corresponding author.
E-mail addresses: nebiyu.girgibo@uwasa.fi (N. Girgibo), xiaoshu.lu@uwasa.fi (X. Lü), erkki.hiltunen50@gmail.com (E. Hiltunen), pekka.peura@uwasa.fI (P. Peura), dzx@jlu.edu.cn (Z. Dai).

http://dx.doi.org/10.1016/j.scitotenv.2023.162599
Received 29 November 2022; Received in revised form 27 February 2023; Accepted 28 February 2023

1. Introduction

Climate change is expected to influence the study area, the Kvarken Archipelago near Vaasa, Finland (Arau'jo et al., 2011). The effect of climate change is displayed mainly through weather pattern changes with seasonal variations. Among those air and water temperatures are expected to rise (Kupiainen et al., 2019). In addition, the same study states that there are expectations of erosion, flooding, land uplift (unique effect in this area) (Girgibo et al., 2022b), strong wind, weather conditions change, the water level rising, precipitation expected to rise and snow depth to decline. Seasonal fluctuation and variations are expected to change for most weather conditions over time (Saranko et al., 2020). Moreover, the other effect of climate change on water systems is indicated by sea level rise (Girgibo et al., 2022b). The importance of this paper is that the investigation of air temperature change's effect on water quality helps understand what kind of changes can be seen in water systems and in what pattern they appear to some extent.

Water quality continuous monitoring has several parameters. In this paper, we are interested in the following parameters Chlorophyll-a (Chl-a), Phosphorous (TP), Secchi depth, Turbidity and water temperature. Chlorophyll-a, as a measure of phytoplankton biomass, is the most often used indicator for quantifying eutrophication by measuring the trophic status of a water body (Kauppila (2007)). Chl-a in water quality analysis is important and is the centre of most parameters' influence. According to Kauppila (2007), using chl-a for water quality assessment, compared to phytoplankton identification and biomass, is cheap and fast for analysis. On the other hand, she described that phytoplankton biomass and species composition estimate could reveal more aspects of eutrophication than chl-a alone, providing more ecological classification metrics. Phosphorous (TP) usually appears in water due to different pollution sources and/or exported from other areas. The actual TP export to the Baltic Sea has remained the same for several years (Räike et al., 2019). Several rivers have shown a decrease in TP because of the discrepancy between the non-normalized and flow-normalized TP, partially due to various mitigation measures to decrease TP concentrations.

Turbidity is a measure of water's cloudiness or lack of clarity resulting from suspended particles or suspensions Wetzel (2001). In technical terms, turbidity is a measure of how much light passes through water and scatter light produced turbidity, which is caused by suspended solid particles (Water-Quality, 2008). Water turbidity restricts the growth of phytoplankton and light penetration limitations in maxima turbidity conditions Kauppila (2007). The type of particles can be microscopic plankton, stirred-up sediment or organic material, eroded soil, clay, silt, sand, industrial waste or sewage (Water-Quality, 2008). In addition, there are several reasons why bottom sediment may be stirred up. Such as waves or currents, bottom-feeding fish, people swimming or wading, or storm runoff (Water-Quality, 2008). In Kauppila (2007) study, the Secchi depth accounts for 16 to 89 % of the variation in chlorophyll-a in Finnish coastal waters and outer water with small chlorophyll-a concentrations. Secchi disk transparency is the mean depth of the point where a weighted white disk, 20 cm in diameter, disappears in water when seen at the top of the water level and reappears when raising Wetzel (2001).

Seasonal variation can affect the level of Secchi disk depth level. The Secchi disk transparencies observation ranges from a few centimetres in turbid waters to 40 m in rare clear lakes (Wetzel, 2001). There is no direct inverse relationship between Secchi depth data with diffuse light attenuation. On other hand, water temperature influences the aquatic species in water bodies. Water's specific heat and thermal energy properties help species survive more easily because water temperature changes happen more slowly in water systems. Climate change influences the water temperature by producing more sun irradiances and higher air temperatures. Climate change is caused by mainly human influences when using fossil fuels for energy sources in different activities.

Climate change has significant impacts on water quality worldwide. Kernan et al. (2010) investigated freshwater ecosystems and found that the biosphere and hydrology cycle are stitched together by freshwater systems. Freshwater systems are a very vulnerable part of the hydrosphere. Climate change will inevitably upset the schemes of aquatic ecosystems as species become eliminated or new ones move into previous cooler habitats (Kernan et al., 2010). Based on these theories, different water quality variables have been studied to assess the impact of climate change. Liu and Wang (2022) investigated the arctic water quality in different rivers by analyzing the total suspended solids in the rivers. Li et al. (2022) investigated the effect of precipitation and Nitrogen on soil microbes. Winder and Schindler (2005) confirmed the influence of climate change on water systems and their species (see also Choo and Taskinen (2015), and Meerhoff et al. (2007)). de Mour et al. (2017) investigated a eutrophic lake located in Central Brazil during a bloom of filamentous cyanobacteria (*Geilterinema amphibium*) by exploring the changes of Chlorophyll-a (Chl-a) concentrations. Kraemer et al. (2022) studied the water qualities for 344 globally distributed large lakes during 1997–2020 using 742 million chlorophyll-a (chl-a) estimates with 6 satellite sensors. Other selected parameters are total phosphorus, total nitrogen, coliform bacteria thermos tolerant, temperature, nitrate as nitrogen, nitrite-nitrate as nitrogen, and Secchi depth.

Bothnian Bay is located in the Gulf of Bothnia and the Kvarken Archipelago is located inside the area of Bothnia Bay. The Kvarken Archipelago is Finland's World Heritage site designated by UNESCO. The purest water in Finland has been universally acknowledged (Ahmed, 2019). A few studies investigated pollution cofounding factors of climate change impacts, for example, hydraulic engineering and sediment technology constructions ((Girgibo et al. (2022a) and Girgibo (2022)), sediment phosphorus (TP) content (Mäkelä, 1986), phosphorus and nitrate trends Fonsellius (1986) and species conditions (Meriläinen (1984), Begge and Meriläinen (1985) and Meriläinen (1988). TP was found to reflect the intensity of engineering around the Kvarken Archipelago area, although TP content can be elevated by floods (Mäkelä, 1986). The same study reported that the first extensive dredging operation revealed an increase of organic carbon in sediment. Several climate/weather factors can affect the mitigation of total TP pollution. According to Fonsellius (1986), there were increasing total phosphorus and nitrate trends in the Gulf of Bothnia, but the phosphate values in Bothnian Bay are extremely low all year round. Furthermore, part of the phosphate in Bothnian Bay might be arsenic: there is a metal ore-smelting plant on the Swedish side of the bay that has been associated with emissions of arsenic. Nitrate concentrations in Bothnian Bay are usually high (Fonsellius, 1986). No significant changes in phytoplankton and chlorophyll-a during the years 1969–1975 and 1979–1983 have been found in the Gulf of Bothnia (Huttunen et al., 1986). The authors of that study recommended that these years´ measurements can serve as a reference period for future studies. After the 1980s there have been improvements in the water quality. Especially, in the Kvarken Archipelago is an unpolluted area at least since the UNESCO protections (Peura and Sevola (1992), Hietikko-Hautala (2012)). This paper extends these studies by collecting much richer data from 61 years from several monitoring stations to investigate the air temperature change effect on water quality in the Kvarken Archipelago in Bothnian Bay. The objective of this paper is to address the following questions:

- Has air temperature change affected well-protected areas like the Kvarken Archipelago? If so, how have these changes impacted water quality? And what are the consequences of water quality variables such as Chl-a concentrations?
- How does the Chl-a level vary over time due to weather effects influenced by climate change? How do changes in other nutrient levels affect Chl-a?

The answers to these research questions will help identify the exact effects of air temperature change on water quality. This study was undertaken to assess expected changes in water quality using long-term historical water quality and climate data. The analysis methods used were mainly Pearson's correlations, linear and multi-regression. Other supporting analyses method were basic statistics, such as normality of data check, skewness and kurtosis interpretation. Our investigation based on these methods indicates that there is a likely effect of air temperature change in a few months on water quality even in the Kvarken Archipelago area. The significance of the study is showing the effect of air temperature change on water quality in the Kvarken Archipelago in a naturally protected area. This shows that the local effects of climate change might differ from the world's expectations.

2. Methods and materials

Fig. 1 illustrates the flow chart of the analysis methods used in this paper. There had been several analyses were conducted which can be classified into data collection, data selection, preliminary analyses, trend analyses and main analyses. Data collection's various section purposes were answering the research questions, getting useful data, protecting and managing the data during the research lifetime and cleaning data, checking its usability and quality. The limitations and drawbacks of the data collection steps were the limited data type present in the local area, taking a very long time to gather the data, not being able to follow it all the time forced to share our data a few times and data combinations generating short data for the most sampling points. The data selection has two major steps: selecting parameters that reflect the best water quality conditions based on limnology theories and using statistically significant relations. These step limitations can focus only on a few parameters with enough data length and only four relations between Chl-a and water quality parameters; air and water temperature were statistically significant.

The preliminary analyses are required to see the water quality status, check the quality of data, see the changes through time, identify the water quality status, and find out the relationships between parameters. Its limitations were, some summary data show wrong results due to outliers in the data, mean trimming was required to see some correct results and too many analysis results cannot be reported in one article. Trend analyses and main analyses have the purposes of investigating the air temperature change effect on the Kvarken Archipelago, investigating the change in water quality data, finding out whether air temperature change influenced water quality data, checking causality relations and trend analyses. These analysis limitations were short data sets and only air temperature able to be used as an indicator of climate change effect among weather change influencers, little water quality variables were able to be used, and no causality was able to be confirmed.

2.1. Data collection and sampling sites

The Kvarken Archipelago is located inside the area of Bothnian Bay. The Gulf of Bothnia comprises the Åland Sea, the Archipelago Sea, the Southern

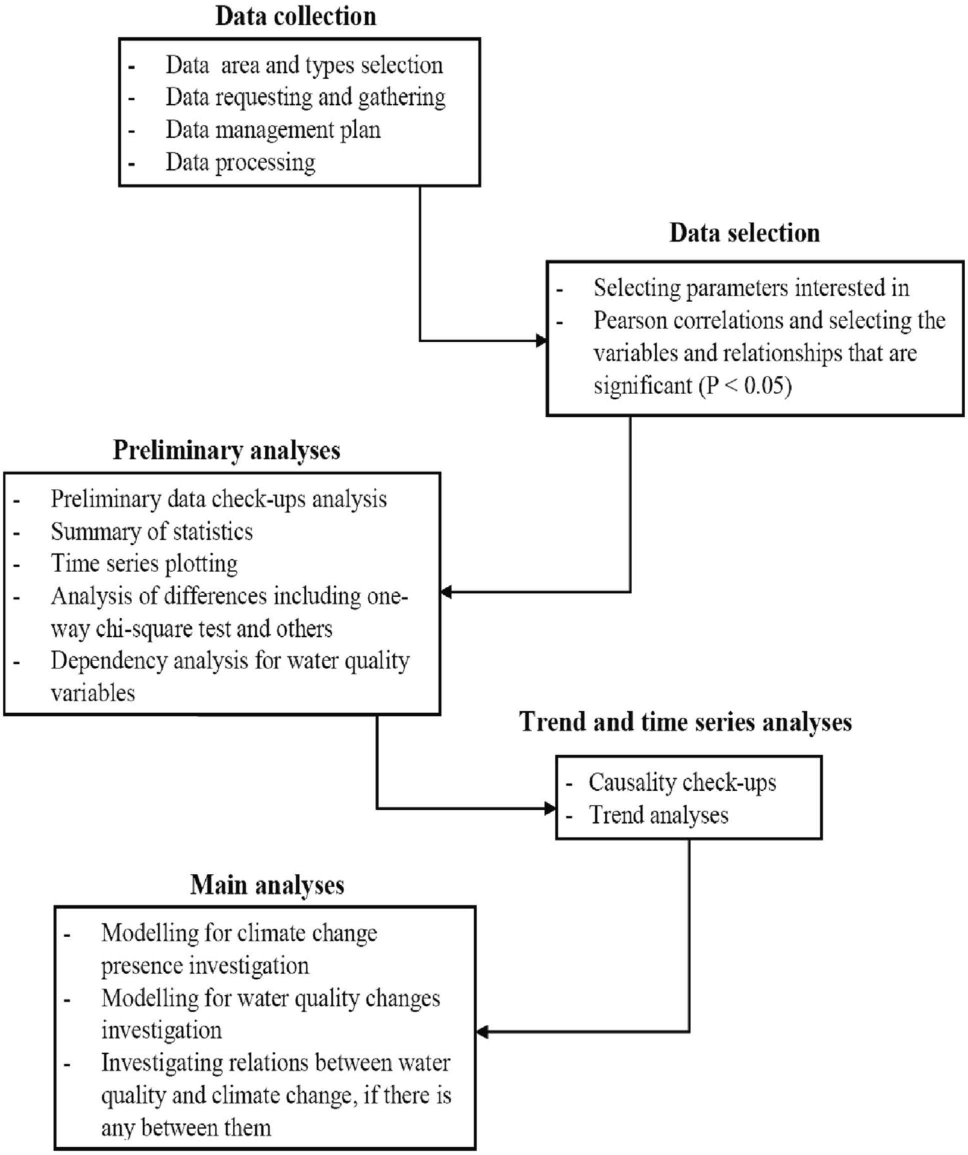


Fig. 1. Flow chart illustrating the analysis methods used.

Quark, the Bothnian Sea, the Quark and the Bothnian Bay (Fonsellius, 1986). The Kvarken Archipelago is a coastal area and archipelago on the east coast of Sweden and the west coast of Finland. The sampling area was around the Kvarken Archipelago in Bothnian Bay, adjacent to the city of Vaasa in western Finland. Fig. 2 illustrates the locations of the six sampling points and the two weather stations for weather data. This study's sampling points are located in Bothnian Bay, close to the Kvarken Archipelago area. The area is far away from the nearest emission sources and relatively unaffected by industrialisation, so its nature is well-preserved (Peura and Sevola, 1992).

Most of the sampling points of water type lie between seawater and inland water mainly these sampling areas are connected to seawater. The analysis standard that was applied was that for seawater, as determined by Suomen Ympäristökeskus (SYKE), the Finnish Environment Institute (Table 2 in supplementary materials). The choice of the seawater standard is logical because all the water samplings are located in seawater. The seawater standard was also applied at the Et. Kaupa 1 (Eteläinen Kaupungin Lahti) site (3f in Fig. 2), even though it is very near to the land. The seawater standard limits are numerically lower, for example in Chl-a than that for inland water. Merten talo (the House of Sea) was a renewable energy installation the project site was presented here because it was a central element for other whole research, which is why the water sampling points builds around it. Now on, Et. Kaupa 1 site is called the 3 f water sampling site. The nearest location 3 f was chosen as a representative sampling site because 1) it is inland water; 2) it has the poorest water quality; 3) it has the longest data compared to the rest of the sampling points; and 4) it has the shortest distance to the weather station. The important reason was that this sampling point was the worst thus any finding can be better than this sampling point result in the same nearby areas. This means any finding from the protected area can be expected to be better so 3 f can show the worst expectations. Other factors can affect the sampling (3f) point. Thus, good exceptions can be found in the protected area, but they cannot be worse than 3 f.

The weather data were gathered from two weather stations over two periods (1959–2011 and 1959–2019) consisting of precipitation amount [mm], snow depth [cm] and air temperature [°C].

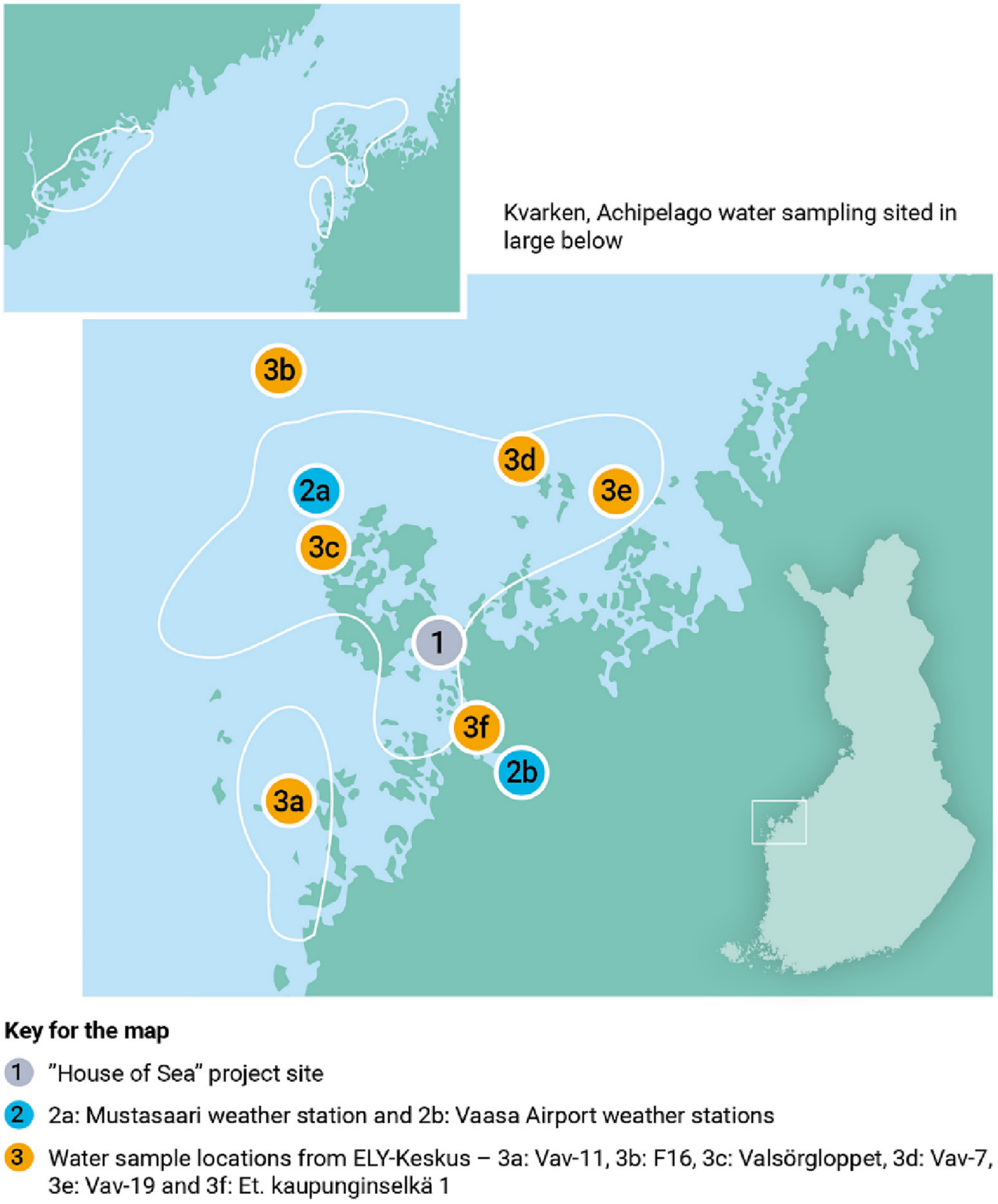


Fig. 2. The map shows the water sampling points, weather stations and the study area. The High Coast/Kvarken Archipelago UNESCO World Protected Site (inside the white line borders). All sampling points near the Kvarken, Archipelago and most inside UNESCO-protected areas (the copyrights of the figure belong to the University of Vaasa, Maria Hällund).

Water quality data were gathered over the period of (1974–2017) including chlorophyll-a [μg/l], total phosphorus, unfiltered [μg/l]; total nitrogen, unfiltered [μg/l]; coliform bacteria thermos tolerant [kpl/100 ml]; temperature [^{o}C]; nitrate as nitrogen, unfiltered [μg/l]; nitrite-nitrate as nitrogen, unfiltered [μg/l], and Secchi depth [m].

The process of sampling in data collection passed through several development processes and specific procedures. No clear sampling procedures are described in the references given to us by ELY-keskus as procedure references. All the collected data qualities were checked and the high-quality datasets from the sampling point 3 f and the Vaasa airport weather station were chosen for analysis. Data processing was done. The two main data processing were removing outlier data and adding missing values were also done during some stages.

2.2. Selections of variables

Pearson's correlation (product-moment correlation) is the data analysis tool to study statistical dependency. The null hypothesis is H_o: the population correlation is zero (= there is no linear relationship). The alternative hypothesis is H_1: the population correlation is not zero. Pearson correlation analysis was conducted between chlorophyll-a and water quality data variables with significant correlations (probability $P < 0.05$), which were chosen to further model the relationships. The chosen water quality and weather variables are total phosphorus (TP), Secchi depth, time (month), turbidity and air temperature vs. water temperature. These selected variables are relevant because they are the basic indicators of changes in water systems and quality. Another reason most of the other parameters were excluded is that while combining the data, only these basic selected variables had enough continuous data to be used in statistical analyses.

2.3. Model eqs

A linear model is performed to test the significance of the temporal changes in the variables:

$$\hat{y} = a_1 + a_{2^*}\ \text{year}$$

where, $\hat{y}$ = predicted variable, a_1 = intercept and a_2 = slope.

SAS Enterprise Guide 7.1. the software was used to calculate the *p*-value and $p \leq 0.05$ rejects the null hypothesis that there is no significance between the two variables.

3. Results

3.1. Preliminary analyses results

3.1.1. Descriptions of data and summary of statistics

Table 1 below lists the key water-quality parameters' mean and standard deviation values for all six sampling points. Variations in values are highly influenced by the sampling period, which is very different at each sampling point. Thus, a slight bias may be introduced because we're not comparing the same number of samples for each point. Among the mean values, the TP and most of the nitrogen analyses show higher values for the 3 f sampling point. This might indicate some kind of local pollution or the influence of the nearby city of Vaasa and the surrounding land. Additionally, the standard deviations of sampling point 3 f show much higher values for most parameters. This suggests the sampling point is affected by its surrounding area or incoming pollution sources. The mean values of the parameters in (Table 1) are compared with the SYKE seawater standard (Table 2 in supplementary materials) later in this discussion of the results, but at this point, the most notable observation is the very high turbidity value at the 3 f sampling point.

These data validate the decision to focus in this analysis on a single sampling point to represent all six points. 3 f has the highest mean and standard deviation values (Table 1), so if this sampling point satisfies the water quality standard, the others will be accepted without further analysis. Furthermore, 3 f is more or less inland water (see Fig. 2) and thus may be expected to exhibit poorer water quality indicators than seawater. The SYKE standard (Table 2 in supplementary materials) illustrates the key differences between expected water quality in lakes/rivers and seawater. Therefore, we are using the worst-case scenario by using 3 f as a single representative sampling point and applying the seawater SYKE standard. The logical descriptive way of comparing and choosing the representative sampling point was done during the statistical analyses.

3.1.2. Water quality and weather data (climate change) variation time series plotting

3.1.2.1. Water quality time series plots. The water-quality variables for the 3f sampling point presented in the following time series are chlorophyll-a, nitrite-nitrate-as-N, coliform bacteria and all-weather data variables. These are depicted in Figures (Figs. 1–3 in supplementary materials): time series data for all the weather parameters are presented in other analysis reports.

Chlorophyll-a time series data shows a clear increase through time (Fig. 1 in supplementary material). This might be due to an increase in nutrients and water temperature through time, most probably influenced or even caused by climate change effects. Some anomalies appear in the years 1980, 1982, 1989, 1993, 2008–2010, 2013 and 2015. Fig. 1 in supplementary materials, also presents the chlorophyll-a (μg/l) time series, but with three- and five-point smoothing for the data. These two data-smoothing tools make the increase in chlorophyll-a through time even more apparent. This merits investigation, particularly about the possibility of a causal link to climate change. The Kvarken Climate Change report (Girgibo, 2021) stated that no algae are blooming near Merten Talo (House of the Sea) in the UNESCO heritage area. Nevertheless, there is a clear increase in chlorophyll-a in this area. The 3 f sampling point is 31 km from the House of the Sea project site, so may show different water characteristics. Pastuszak et al. (2018) observed that “eutrophication can happen even in low phytoplankton level waters,” so eutrophication may be present in this area, even if there is less Chl-a concentration.

Plots of phosphorus show that this parameter also seems to be increasing through time, with a notable anomaly in the early 1980s. There is a similar anomaly seen in nearly all the graphs of water-quality parameters, which is most probably due to the effect of the 1970 -1980s industrial revolution. The TP level has been growing since 2000, possibly due to the effect of climate change. There is some similarity between the growth of chlorophyll-a and TP through time. This may also show that the TP is affecting the Chl-a concentration. However, the forecast found after this analysis TP is expected to decline over time, but these time-serious data were based on observed data only plotting it manually in excel.

The TN data show many fluctuations and anomalies. The most recent, in 2012, seems less marked than some in the1980s, 1992 and 2004–2006. The TN data do not show a clear incremental increase. However, an increase through time is evident in Figure (Fig. 2 in supplementary materials), depicting nitrite-nitrate-as-nitrogen. Thus, the different nitrogen types exhibit different patterns.

The concentrations of nitrite-nitrate-as-nitrogen begin to show higher values in the years following 1992. The change in this parameter seems to contribute to changes in TN level during the same period. Both nitrite-nitrate-as-nitrogen and TN show higher values in 1996–1998 and 2012–2016: the cause of this is worthy of investigation.

The concentration of coliform bacterium (thermotolerant) has declined over time (Fig. 3 in supplementary materials). This improvement in water quality is most probably due to increased efforts to avoid pollution, especially as the water sampling point is close to the city. This downward trend runs counter to the upward trend of the other nutrients. The climate change effect and water quality improvement are possible explanations for this discrepancy. The highest coliform bacterium concentrations occurred in 1974–1984, a time of rapid industrial development when it was common to dispose of waste in water bodies.

Table 1

Mean and standard deviation values of parameters for all water-sampling points. Sampling point names and numbers (similar names in Fig. 1) were kept in brackets.

	Mean (M) ± Standard deviation (SD) (range)					
Sampling parameters	Et kaupa 1 (3f)	F16 (3b)	Valsörsgloppet (3c)	Vav-7 (3d)	Vav-11 (3a)	Vav-19 (3e)
Average sampling depth	0.784 ± 0.242 (0–1)	0.167 ± 0.375 (0–1)	3.471 ± 1.718 (1–5)	–	–	–
Faecal enterococci (pcs/100 ml)	3.391 ± 7.422 (0–40)	–	–	–	–	–
Oxygen saturation (yes. %)	87.844 ± 19.787 (22 − 123)	102.4 ± 10.574 (91–115)	97.529 ± 5.088 (90–112)	97.118 ± 8.105 (63–132)	97.423 ± 6.504 (65–125)	97.308 ± 6.277 (72–114)
Dissolved oxygen (mg/l)	9.828 ± 1.674 (3.2–13.3)	11.691 ± 1.6 (9.1–14.7)	10.9 ± 1.853 (8.4–14)	11.079 ± 1.904 (8.3–14.6)	11.215 ± 1.671 (7.5–15.3)	11.213 ± 1.496 (7.5–14.6)
Chemical oxygen demand mg / l	–	–	5.58 ± 2.097 (3.9–8.8)	–	–	–
Suspended solids, fine, filtration polycarb. 0,4 μm mg/l	–	–	–	–	–	1.347 ± 0.878 (0.5–3.2)
Suspended solids, coarse (mg/l)	18.291 ± 17.663 (4.4–60)	–	–	–	2.065 ± 0.705 (0.5–3)	1 ± 1 (1)
Chlorophyll a (μg/l)	7.68 ± 5.97 (0.3–36)	3.417 ± 1.963 (2.3–7.4)	1.954 ± 0.905 (0.4–3.1)	2.389 ± 0.781 (0.8–4.3)	2.863 ± 2.227 (0 − 21)	2.791 ± 1.358 (0 − 10)
Total phosphorus, unfiltered (μg/l)	20.89 ± 19.003 (2–218)	7.284 ± 4.024 (1.6–22.6)	11.553 ± 5.048 (4.7–28)	10.647 ± 5.568 (4–50)	14.567 ± 5.336 (6–57)	10.502 ± 6.1 (3–69)
Totalt nitrogen, unfiltered (μg/l)	1118.851 ± 1013.358 (140–6700)	259.839 ± 132.627 (165–1188)	274.118 ± 79.613 (170–420)	308.404 ± 126.153 (170–1300)	281.286 ± 54.943 (110–550)	407.191 ± 219.384 (130–2800)
Coliform bacteria thermotolerant (kpl/100 ml)	11.263 ± 22.861 (0 − 130)	–	–	–	–	–
Water temperature (°C)	11.885 ± 7.414 (−0.2–24)	8.164 ± 5.553 (−0.3–17.7)	10.353 ± 7.61 (−0.2–22.2)	9.445 ± 7.727 (−0.3–22.2)	8.80 ± 5.65 (−0.3–21.9)	9.127 ± 5.985 (−0.3–21.7)
Nitrate as nitrogen, unfiltered (μg/l)	300.793 ± 607.684 (2 − 3100)	1.267 ± 1.176 (0–4)	28.272 3 ± 37.59 (2 − 110)	83.063 ± 110.651 (5–640)	58.423 ± 54.964 (0–250)	209.52 ± 137.867 (70–630)
Nitrite as nitrogen, unfiltered (μg/l)	1.88 ± 2.403 (0 − 11)	–	–	1.969 ± 0.897 (1–5)	2.756 ± 6.953 (0–61)	2.36 ± 0.7 (1–4)
Nitrite nitrate as nitrogen, unfiltered (μg/l)	456.253 ± 697.891 (2–2900)	41.544 ± 30.975 (1 − 110)	–	56.542 ± 52.105 (2–140)	27.76 ± 42.093 (0–190)	146.622 ± 147.67 (2 − 1000)
Secchi depth (m)	1.295 ± 0.534 (0.2–2.5)	5.25 ± 0.987 (4–7)	4.553 ± 1.305 (0.6–5.8)	3.957 ± 0.933 (2.2–6.5)	3.227 ± 0.971 (0.35–8)	3.721 ± 1.321 (0.4–11)
pH	7.149 ± 0.882 (4.3–8.4)	7.994 ± 0.139 (7.6–8.31)	7.806 ± 0.09 (7.7–8)	7.712 ± 0.234 (6.9–8.2)	7.816 ± 0.225 (6.7–8.4)	7.637 ± 0.271 (6.5–8.1)
Salinity (‰, salinity unit)	3.252 ± 1.15 (0.1–5.1)	3.96 ± 0.45 (3.2–5.41)	3.998 ± 0.527 (3.4–4.88)	3.691 ± 0.402 (3–5.68)	5.014 ± 0.467 (1.82–6.05)	3.301 ± 0.36 (1.06–5.5)
Turbidity (FNU)	5.447 ± 6.417 (0.46–42)	–	0.681 ± 0.315 (0.31–1.7)	0.744 ± 0.321 (0.15–2)	1.726 ± 1.217 (0.1–9.8)	1.407 ± 1.671 (0.1–19)
Conductivity (mS/m)	582.916 ± 184.866 (25.6–880)	–	717.733 ± 84.98 (610–870)	666.667 ± 57.451 (560–830)	891.343 ± 66.039 (680–1060)	605.077 ± 54.595 (210–750)

3.1.2.2. Weather data (climate change) time series plots. All the weather data were gathered from two weather stations: Vaasa airport and Mustasaari.

3.1.2.2.1. Vaasa airport weather station data. The average air temperature at Vaasa airport. From 1959 to 2011 the temperature has been between a maximum of 25 °C in summer and a negative (−) 30 °C in winter. The data do not show any change through the time when plotted in this manner. However, the removal of seasonal cycles reveals additional information. Air temperature can be expected to increase due to global warming, influencing various parameters of water quality. However, the influence of air temperature on water temperature is not clear: it seems that there is a delayed effect. Further investigation is studied later, showing the expected influence of climate change on quality in water bodies.

The rainfall appears to have random fluctuations rather than a pattern, but also shows seasonal fluctuations. Removal of seasonal variations is expected to show other patterns. Such as increments through the time of rainfall in the local area. Some seasons show extremely high precipitations, which is normal. The majority of the data are below 25 mm of precipitation, but with some outliers in at least two seasons´ precipitation. There does not appear to be a clear increase or decrease in rainfall over time. Based on collected data, Girgibo (2021) and forecasts by others point towards the likelihood of increasing rainfall all over Finland in the far future.

In addition to the normal seasonal fluctuations, the snow depth data also seem to show some cyclical events, with greater depth in some decades than in others. The depth was low from 2000 to 2011 but unfortunately, there are no data for this site from the Finnish Metrological Institutes (FMI) for the years after 2011. This time series data does not show a clear decline or increase in snow depth. Other findings are possible after removing the seasonal cycles. Such as the decline of snow depth through time. The other measurements for Vaasa airport weather station (lowest air temperature and highest air temperature) show only the natural fluctuations and so have not been plotted.

3.1.2.2.2. Mustasaari weather station data. Some small increase in average air temperature through time is apparent in the Mustasaari weather station data. However, further analysis must be done after removing the seasonal variations. Such as the increment of air temperature in the local area. The lowest temperature in Mustasaari is between zero and minus 20 °C, whereas in Vaasa airport station the lowest temperature reaches minus 30 °C. The proximity of Vaasa airport weather station to urban areas may be expected to result in higher temperatures than at Mustasaari, but this does not seem true for the coldest temperatures. The coldest temperature at Mustasaari seems to exhibit a decadal cycle, which can be normal natural fluctuations.

The lowest air temperature seems to increase over time at the Mustasaari weather station. However, the highest air temperature appears to show normal fluctuations. The coldest temperatures in this lowest air temperature seem to have a decadal cycle, as was noticed in the average air temperature at Mustasaari. More can be discovered after removing the seasonal cyclic changes in this data. After the removal of seasonal cycles, it is possible to see an increment or decrement in the air temperature in the local area.

The rainfall seems to show natural fluctuations, with occasional severe rainfall. Rainfall is changing over time and some articles state that winter rainfall is increasing in Finland. It should be possible to test this statement by separating winter and summer rainfall data, but the available data was not suitable for this. However, the forecast of air temperature was built by modifying seasonal variations and lags in modelling and this shows a clear increment through time. The snow depth graph from Mustasaari depicts a decrease in recent decades, but with a spike in snowfall in 2019. The snow depth data from both weather stations show a decadal cycle, with this pattern being more clearly exhibited in the data from Vaasa airport.

3.1.3. Water quality status checking by one-way chi-square analysis

3.1.3.1. Comparing the 3f sampling point data with the SYKE standard. Table (Table 2 in supplementary materials) presents the various limits for the parameters used by SYKE (Suomen Ympäristö-keskus/Finnish Environment Institute) to assess the water quality of lakes, rivers and sea areas in Finland (SYKE, 2003).

3.1.3.2. One-way chi-square analysis. One-way chi-square analysis was used to evaluate the data against the SYKE seawater standard. The seawater standard, instead of the lake/river standard, was used because its limits for Chl-a and TP are more stringent, so complying with this also will satisfy the lake water standard. There were around 322 samples taken during the period from 1974 to 2017, equating to an average of at least two samples per year, so these results are sufficient for an adequate representation of the long-term picture.

Figure (Fig. 4 in supplementary materials) shows how the sample results are distributed across the SYKE seawater standard for Chl-a. Of the 322 water samples, 4.04 % were found to satisfy the SYKE's Excellent rating for seawater. However, 320 samples included are replaced by satisfactory level (3) for those sampling periods missing. >50 % of the data is missing value if we assume 34.84 % is the satisfactory sampling period. Almost 204 samples or 74.84 % are represented by satisfactory levels including the missing values. Crucially, only 0.62 % of the samples have a Poor rating (level 5) for Chl-a concentrations. The remaining 33 % - around 100 samples – have either Good or Passable ratings (levels 2 or 3) for Chl-a concentration.

Despite the sampling point 3 f´s proximity to land at this Chl-a level satisfies the seawater standard and is better than lake water quality. Against the null hypothesis of equal cell frequencies, the chi-square value is 616.3851. Degrees of freedom (d.f.) are calculated as k–1 where k is the number of categories. With five categories in the present example, there are four d.f. With four d.f. the chi-square value is likely to occur with a probability (Probability > Chi-Sq) of <0.0001 if the null hypothesis is true, which is statistically significant against the alpha level of $\alpha = 0.05$ (5 % statistical significance). One can therefore conclude that the five possible seawater standards used to classify Chl-a data were not mate equally for Chl-a at the sampling point of the 3 f sampling point. Using the Chl-a concentration as representative of water quality shows that the water is at least in satisfactory condition.

Figure (Fig. 5 in supplementary materials) shows how the samples are ranked against the SYKE seawater standard for TP. Of the 322 samples, 25.78 % are classified as Excellent. However, 320 samples included are replaced by satisfactory level (3) for those sampling periods missing. The missing values do not seem a lot in TP data compared to that of Chl-a data. Most of the other water quality variables were found to be at a good level. Therefore, it is possible to justify that the missing values do not influence the assumption of the data is satisfactory level. Almost 125 samples (40.06 %) are ranked as Satisfactory (level 3), including the missing values. Only 0.62 % of the samples have a Poor rating (level 5) for TP concentrations. The other 180–190 samples are either Good (27.02 %) or Passable (6.52 %).

The null hypothesis of equal cell frequencies, the chi-square value, is 167.814. With five categories in the present example, there are four degrees of freedom (d.f.). With four d.f. the chi-square value is likely to occur with a probability (Probability > Chi-Sq) of <0.0001 if the null hypothesis is true, which is statistically significant against the alpha level of $\alpha = 0.05$ (5 % statistical significance). We can therefore conclude that the five possible seawater standards used to classify TP data were not mate equally for TP at the sampling point of 3 f. The water is at least in satisfactory or passible condition when using TP as an indicator of water quality.

Figure (Fig. 6 in supplementary materials) depicts the frequency of sampling results across the SYKE standard´s three ratings for transparency (Secchi-depth). Excellent quality (level 1) was observed in just 0.62 % of the 322 samples. However, 320 samples included are replaced by satisfactory level (3) for those sampling periods missing. The missing values do seem much in transparency (Secchi-depth) compared to others. Most of the other water quality variables were found to be at a good level. Therefore, it is possible to justify that the missing values do not influence the assumption of the data is satisfactory level. Almost 145 samples (44.41 %) are Satisfactory (level 3), including the missing values. The remaining 54.97 % are classified as Good (level 2).

Against the null hypothesis of equal cell frequencies, the chi-square value is 160.44. With three categories in the present example, there are two degrees of freedom (d.f). With two d.f. the chi-square value is likely to occur with a probability (Probability > Chi-Sq) of <0.0001 if the null hypothesis is true, which is statistically significant against our alpha level of $\alpha = 0.05$ (5 % statistical significance.) We can therefore conclude that the three possible seawater standards used to classify Secchi depth data were not mate equally for transparency (Secchi depth) at the sampling point of 3 f. In other words, the water quality is at least in a satisfactory condition when using transparency (Secchi-depth) as the parameter.

The SYKE standard has only two classifications for turbidity: Excellent (level 1) and Good (level 2). 54.66 % of the samples were ranked as Good: and 45.34 % were rated as Excellent. Against the null hypothesis of equal cell frequencies, the chi-square value is 2.795. There is one degree of freedom with two categories in the present example. With one d.f. the chi-square value is likely to occur with a probability (Probability > Chi-Sq) of <0.0946 if the null hypothesis is true, which is statistically significant. The good quality standard classification was more often than the excellent water quality standard classification for turbidity. In other words, the water quality is at least in good or below conditions when using turbidity as a water quality check-up.

3.1.4. Water quality analysis (additional statistical dependency analysis)

The central variable in this study of water quality data is chlorophyll-a (Chl-a), which is an indicator of the amount of phytoplankton present in water systems. This is influenced mainly by nitrogen and phosphorus. The five relations show a linear relationship at 5 % ($P < 0.05$) statistical significance are: 1. Chl-a and TP; 2. Chl-a and Secchi-depth; 3. Chl-a and month; 4. Chl-a and turbidity; and 5. water-temp and air-temp. The other correlations analysed showed no linear relationship. The summary of these results and relationships is presented in the next Table 2.

3.2. Trend and time-series analyses

The air temperature vs. years is weather data, and this weather data was collected from Vaasa airport weather station from Finnish Meteorological Institute (FMI) database. The sum of temperature per year starting from 1974 to 2010. The basic anomaly observed was similar to the water temperature and Chl-a analysis where 1974 and 1998 years show lower values and the rest show higher values in this bar chart. These two-year anomalies were also observed inline plot chart for observed data. These results show lower values for these two years. This fact means that in these two years,

Table 2
Pearson's correlation summary for water quality variables and weather data from Vaasa airport. The results presented here are statistically significant (rejecting the null hypothesis). (P = probability ($P < 0.05$)).

	Chl-a	Water temp.
TP	0.55794, $P < 0.0001$	–
Secchi depth	−0.55085, $P < 0.0001$	–
Month	−0.25609, $P = 0.0053$	–
Turbidity	0.43998, $P < 0.0001$	–
Air temperature	–	0.89691, $P < 0.0001$

the air temperature was lower, which is why changes were noticed in the rest of the variables. In the forecasted data there is the expectation of a very high air temperature in the year 2033. This result is also the driver of changes noticed in the other variable charts of forecast data for 2033. The rest of the forecasted years seem to have higher values than the observed data bar chart. The anomaly for the year 2033 is also seen clearly in the line plot for forecasted air temperature data. The seasonal fluctuation was noticed both in observed and forecasted data line plots. These results are expected because both data were not treated for lags and/or seasonal variations corrections. These trend analyses show that there is a clear connection between variables. This result means the data and its analyses were not robust. The air temperature was the driver of all variables, although other variables' contributions influenced some variables.

For Chlorophyll-a (Chl-a) vs years observed and predicted data values show variations and anomalies. Except in 1998, all yearly sums of data from 1978 until 2010 show increments through time with some year fluctuations. The line graph shows an anomaly (decline in the amount of Chl-a). Otherwise, the observed data shows a clear inclination in Chl-a throughout the years. This result shows that higher values are expected in predicted data from June 2022 to February 2042. Thus, one can conclude that all trends for Chl-a vs year show a clear increment through time. The line plot of Chl-a predicted data shows an anomaly in about the year 2033. This year also noticed other analyses that have expected to show a different pattern than the rest of the predicted data. There is nothing real theory about what can happen in the year 2033, but this has shown higher fluctuations in expectation for various variables plot. The years 2023, 2025 and 2037 show some anomalies (inclinations). There are no clear explanations for those years of anomalies too. Generalizing, Chl-a vs year trend analysis, one can say that it shows a clear inclination both in observed data and predicted data.

Water temperature vs year observed data shows a lower amount of sum per year temperature in the years 1974 and 1998. As noticed in the line plot, the water temperature was above 5 °C on average in all the years from 1970 to 2010. The line plot also shows a lower value anomaly for the year 1998. The fluctuates noticed were because of seasonal variation causing the temperature to be positive or negative. The FMI (Finnish Meteorological Institute) website mentioned that the winter of 1998/1999 was average, and on February 11th' there was its largest extent of ice in Bethania bay. The forecasted data shows a continuously higher temperature sum per year than the observed data. In some years, the sum of temperatures was higher in the observed data bar chart. The seasonal variation was seen both in observed and forecasted data. The forecasted data was prepared before lag and seasonal correction in modelling procedures. Therefore, the seasonal variations were also expected to be seen in the forecasted data line plot. The year 2033 anomaly seen in Chl-a vs year line plot chart was not seen in this water temperature vs year line plot chart. It was expected to see similar patterns because they employ similar data sets.

There is less observed data for Snow-depth. It was seen that the Snow-depth values were highest from 1980 to 1989. The collected data was from 1974 to 1995. The forecasted data shows a Snow-depth decline over time. It was seen a significant decline in Snow-depth after March 2028. It is also seen in the forecasted data there is no Snow-depth value starting from 2033.

The industrial revolution in history has influenced water bodies significantly in the past. However, nowadays, its influence has been declining much more significantly. This result shows the growth in environmental protections and better world environment management compared to the past. However, it is not clearly shown in the analyses for TP. This result is because the data collection started in 1974. However, the industrial evolution time was before 1970. This data collection was started probably due to the growth in awareness for controlling pollution in water bodies and the environment. In the bar yearly sum vs year chart of observed data for the TP chart, it was noticed that the highest value is for 1982. The rest show lower values. The line plot also shows a similar pattern. Comparing the observed data charts with the forecasted data charts, one can conclude that there is no clear increment through time. However, there was an anomaly in the year 2023 with the highest bar chart values and line plots for forecasted data. In the line plot for forecasted data, a higher value of TP was observed between 2022 and 2025. The rest show normal fluctuations. Bar yearly sum vs year chart, also shows normal fluctuation, no increment or decrement. Therefore, we have concluded here that there is normal fluctuation to be expected in future values of TP on this site.

If we compared the Turbidity and Secchi-depth charts, it is clear that those years that recorded lower amounts of Turbidity show higher Secchi-depth as expected. The yearly sum for 1990, 2002, and 2006 was higher, as seen in the bar chart. The lowest values were found in 1974 and 1998. This result is probably due to short observed values because Turbidity also showed lower values in these years. However, Secchi-depth also showed lower values; thus, the only explanation can be the shortage of data in these years to show lower values. Similar patterns were observed in other variables of lower values in these years. The line plot for observed data showed the highest values in 1979–1992 and 2007. The lowest values are noticed in this line plot for the years 1981 and 1998. The forecasted data bar yearly sum and line plot show higher values. This result is showing somehow higher values for Secchi-depth in the future. This result is a bit unexpected because the Turbidity data forecast also shows an increment in future. One point to notice was that the Secchi-depth increment forecast is higher than that of the Turbidity forecast. Therefore, there is an expectation of a higher Secchi-depth than Turbidity. Seasonal variations can explain the fluctuation noticed in the forecasted data line plot. The bar yearly sum vs year chart shows higher values in the middle years, and it is the opposite pattern compared to the Turbidity bar yearly sum vs year chart.

Bar yearly sum vs years for observed data shows that the values in the years 1974 and 1998 are low. A similar pattern was also noticed in the other variables for these years. The year 1982 shows the highest Turbidity compared to the rest of the observed data. The line plot for observed data shows a similar pattern as that of the yearly sum bar chart, even though the value was lower because they do not show the yearly sum. The highest values observed in this observed data line plot were in 1977 and 2010. Moreover, the lowest value noticed in this line plot was in the year 1978. There is no clear increment or clear decrement in all of the charts. There is an expectation of many fluctuations, as seen in the forecast. The bar yearly sum vs year for forecasted data shows somehow U shape structure. This result means it has a higher value at the beginning of the forecast years, then declines in the middle and rises at the end of the years. There are no clear explanations for why the bar chart created this shape. A similar pattern is noticed inline plot for forecasted data. The line plot showed a lot of fluctuation. This most probably had been influenced by seasonal variations. The years 2021, 2023 and 2039 showed the highest values seen in the line plot. The opposite result is noticed in Secchi-depth (transparency). Hence, turbidity and Secchi-depth show opposite characteristics of the same water body.

3.3. Main analyses results: linear and multiple regression analyses

3.3.1. Weather data change investigations and descriptions

Climate change in short can be defined as a change in the state of the climate that can be distinguished by statistical tests (Girgibo, 2021). In this paper, the air temperature change effect is investigated in weather data by statistical analyses, which is linear regression. First, we try to show that there is a change in air temperature in near areas of the city of Vaasa for at least a few months. Afterwards, the water quality changes investigations in two main parameters, which are Chl-a and water temperature. Then the relationship between water quality and air temperature is presented.

Air Temperature (weather pattern change): the result shows for seasonally corrected data that the coefficient of determination (R^2) is 0.0181, so only about 1.8 % of the total variation in Air temperature can be explained by this regression model. The percentage of data explained is very low. Its trustworthiness is very questionable.

So, as one-year increases, increases the value of Air temperature is on average by 0.20158 amount. Because the probability of the model is 0.0334 and which is <0.05 (5 % significance level), we can now reject the H_0 for the explanatory variable. R^2 is <2 % of the data explained by this analysis we concluded that there is not enough evidence to confirm the presence of the significant effect of climate change in the area in continuous years at every month together. However, in the Months of April and July, there were statistically significant air temperature changes in the Kvarken Archipelago area. The R^2 for April was 0.2109 or the model explains a 21.09 % increase in Air temperature. For July R^2 was 0.1207 or the model explains a 12.07 % increase in Air temperature throughout the data collection period (see Fig. 3). This means there are changes in air temperature in the months of April and July based on our data sets analysis. The next Table 3 presents the yearly average each month air temperature intercept, slope, R2 and P > F each from 1959 to 2011.

3.3.2. Water quality change investigations and descriptions

The two indicators used for water quality are chlorophyll-a and water temperature investigation results given below. The indirect causality path that is indicated that air temperature influenced the water temperature and further through indirect paths influence the growth and abundance of phytoplankton biomass indicated by chlorophyll-a concentration. However, this indirect causality was not confirmed due to multicollinearity in the data.

Chl-a (Chlorophyll-a) (water quality changes): the result shows for seasonally corrected data that the coefficient of determination (often denoted R^2) is 0.0067, so this regression model can explain only 0.6 % of the total variation in Chl-a. The percentage of data explained is very low. Its trustworthiness is very questionable.

So, as every one-year increase, increases the value of Chl-a on average by 0.04779 amount. Because the *p*-values are 0.2128 and which is >0.05, not statistically significant based on the seasonally corrected data set. We can now accept the H_0 for the explanatory variable. The linear regression model does not exist for each month. However, a statistically significant increase in years was seen in the months of May, June, July, August, September and December (See Table 4 for the results).

Table 3
The data sets analysis results for linear trend fitting: intercept, slope, R^2 (goodness-of-fit) and P > F (model probability) for air temperature. Model: $\hat{y}$ = a1 + a2*year and only the statistically significant (*P < 0.05*) results are presented here.

Original Vaasa airport data set/ observed data 1959–2011				
Yearly averaged monthly air temperature (1959–2011)	Intercept (a1)	Slope (a2)	R^2	P > F
April (48 years of data in number)	−87.29270	0.04515	0.2109	0.0009
July (49 years of data in number)	−46.31031	0.03144	0.1207	0.0155

Additional data mining shows that the result for chl-a regression is

$$\hat{y} = 9.63156 + 0.03725^{*}\text{ Phosphorous} - 2.73417^{*}\text{ Secchi Depth} + 0.06193^{*}\text{ Turbidity}$$

where, $\hat{y}$ = Chl-a.

Water temperature (water quality changes): the result shows for seasonally corrected data that the coefficient of determination (R^2) is 0.0180, so this regression model can explain only about 1.8 % of the total variation in Water temperature. The percentage of data explained is very low. Its trustworthiness is very questionable (See Table 5 for this result).

So, as one-year increases, increases the value of water temperature on average by 0.10764 amount. Because the *p*-values of the model are 0.0340 and are <0.05 (5 % significant level), we can now reject the H_0 for the explanatory variable. R^2 <2 % of the data is explained by this analysis we concluded that there is not enough evidence to confirm the presence of the water temperature increase in the area each month. However, as the following equations show for February, March, June and July there are statistically significant results. Please see Table 4 for the whole water temperature and Chl-a analysis results, which are statistically significant.

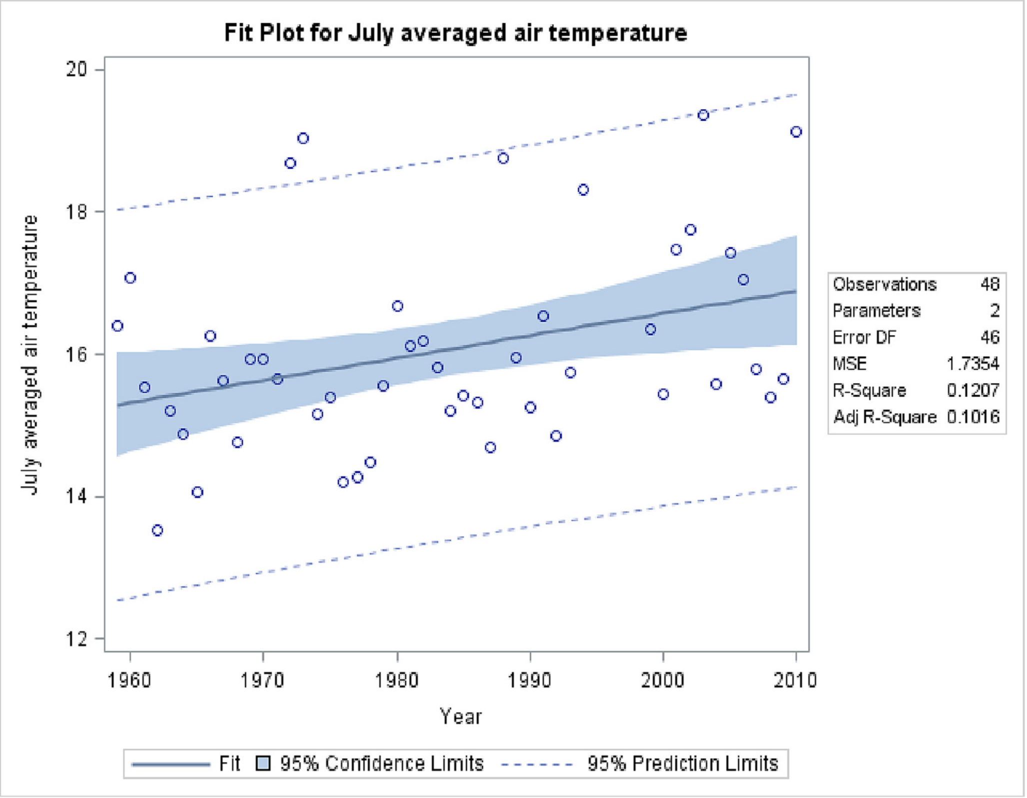


Fig. 3. July averaged per year data with regression line.

Table 4
The data sets analysis results for linear trend fitting: intercept, slope, R^2 (goodness-of-fit) and P > F (model probability) for water temperature. Model: ŷ = a1 + a2*year and only the statistically significant at (*P < 0.05*) results are presented here.

Original 3f data set averaged/ observed data 1974–2017				
Yearly averaged monthly water temperature (1974–2017)	Intercept (a1)	Slope (a2)	R^2	P > F
February (only 10 years of data in number)	653.31373	- 0.32290	0.6137	0.0073
March (only 28 years of data in number)	- 453.26039	0.22876	0.2660	0.0050
June (only 31 years of data in number)	−203.12336	0.10949	0.1304	0.0459
July (only 37 years of data in number)	−259.60625	0.13850	0.1199	0.0357
Yearly averaged monthly Chl-a (1974–2017)	Intercept (a1)	Slope (a2)	R^2	P > F
May (only 14 years of data in number)	−719.47951	0.36341	0.5401	0.0028
June (only 29 years of data in number)	−773.07902	0.39101	0.4685	<0.0001
July (only 36 years of data in number)	−390.57200	0.19874	0.2671	0.0013
August (only 23 years of data in number)	−226.52421	0.11656	0.1747	0.0472
September (only 11 years of data in number)	−753.02839	0.38007	0.4454	0.0249
December (only 9 years of data in number)	−719.59573	0.36407	0.6187	0.0119

Also, the pictures for air and water temperature analyses are found in supplementary materials in Figs. 7–11.

The statistically significant monthly ($P < 0.05$ or 5 %) results for water temperature are displayed in the next formulas.

- ŷ (February) = 653.31373–0.32290*year (R^2 = 0.6137, P model = 0.0073)
- ŷ (March) = − 453.26039 + 0.22876*year (R^2 = 0.2660, P model = 0.0050)
- ŷ (June) = −203.12336 + 0.10949*year (R^2 = 0.1304, P model = 0.0459)
- ŷ (July) = −259.60625 + 0.13850 year (R^2 0.1199, P model = 0.0357)

Where, ŷ (m) = water temperature (in the month).

3.3.3. Relationships between water quality and climate change

The relationships between water quality and air temperature were investigated by checking the correlation and multi-regression between water and air temperature. This relationship is not a direct path for most parameters of water quality influenced by climate change. However, there is a clear direct relationship between air temperature influencing water temperature as shown in the next multi-regression result.

Air temperature and water temperature: Positive relations of regression line best-fit plotting were found for air temperature and water temperature. Fig. 12 in the presentation of the supplementary materials explains 80 % (R-square = 0.8044) of the data in the analyses. This is the result is expected because both variables explain the same variable, which is temperature.

Comparing various multi-regressions formulas, it was found that for all the combined variables, the formulas show differences between original/observed data and forecasted prepared time series data. This article aims to show that these changes in water quality parameters are due mainly to changes in air temperature (see Fig. 12 in the supplementary materials), influenced by global warming or climate change.

It was found that the presence of climate change in the area cannot be confirmed for each month. This might be due to the shortage of the period where the data is collected and seasonal variations. Based on theories and other world areas' expectations the effect of climate change is very real in most parts of the world. This was in air temperature change for the months of April, and July for air temperature and the water temperature in the months of February, March, June and July were statistically significant as shown in Tables 3 and 4.

4. Discussions

It was expected that Chl-a and Secchi depth would have opposing trends, but they both have an upward trend. However, the Secchi depth trend fluctuates and is not a straight upward trend. This probably derives from the Chl-a fluctuations in the original data, and is not clear in this forecast analysis because of seasonal factors and lag removal. The theoretical explanations stated that global warming is accompanied by increasing phytoplankton concentration (chlorophyll-a amount) in current and future water systems. This might show causality relations, but these cannot be proven, for example by using structural equation modelling (SEM). There is multicollinearity between variables, which is one of the limitations of SEM analysis.

Some dependent relations between different water quality parameters and weather data. Dr. Petri Välisuo used Bayesian networks and Pomegranate modelling software to investigate the preliminary relationships within the data. The work used 100 data points, drawn from 2004 to 2018. The arrows shown in Bayesian networks do not show the causality relation according to Pearl and Mackenzie's (2018) causality description book. Our analysis finding indicates that oxygen saturation is dependent on month and temperature; chlorophyll-a is dependent on oxygen and nutrients, and turbidity is dependent on chlorophyll-a and Secchi depth. There is a clear dependency of one parameter on another. The main effect of weather data seems through air temperature affecting ➔ water temperature and this, in turn, affecting ➔other water quality variables. This might show

Table 5
The two data sets analyses result for linear trend fitting, intercept, slope, R^2 (goodness-of-fit) and P > F (model probability). All R^2 results were found to be very low. Model: ŷ = a1 + a2*year and bold results are statistically significant (*P < 0.05*).

	3f original data set/ observed data (1974–2017)				3f observed data/seasonally corrected data (1974–1994)			
The whole period of data Model: ŷ = a1 + a2*year	Intercept (a1)	Slope (a2)	R^2	P > F	Intercept (a1)	Slope (a2)	R^2	P > F
Chl-a	**- 477.836**	**0.24304**	**0.1978**	**< 0.0001**	- 88.73758	0.04779	0.0067	0.2128
Phosphorous	**593.03797**	**- 0.2831**	**0.0255**	**0.0304**	**920.18657**	**- 0.45300**	**0.0559**	**0.0002**
Secchi depth	8.30957	- 0.00346	0.2905	1.57164	1.57164	−0.00005334	0.0000	0.9866
Turbidity	- 12.12905	0.00829	0.0004	0.7904	13.91197	−0.00486	0.0001	0.8821
Water temperature	- 151.44406	0.08183	0.0137	0.0805	**- 202.74471**	**0.10764**	**0.0180**	**0.0340**
Air temperature (1959–2011)	- 155.49392	0.08240	0.0083	0.1685	**- 390.32824**	**0.20158**	**0.0181**	**0.0337**

causality, but that must be proven by other analyses before concluding there is a clear causal relationship between climate change and water quality, through the weather. Chl-a and oxygen saturation; Chl-a and dissolved oxygen; and Chl-a and TN do not show statistically significant linear correlations. They might have some other polynomial correlations or they probably act by affecting other parameters that are important for the growth of phytoplankton.

The figure presented by Pastuszak et al. (2018) shows more relationships between different aspects of a water body. This point is essential in understanding the complexity of using Chl-a as an indicator of phytoplankton concentration, and then further used to evaluate the status of water and eutrophication. Lakes can be eutrophic but still with a low concentration of Chl-a (oligotrophic or mesotrophic) (Pastuszak et al., 2018). However, the water sampling places in this study are not that deep water. Therefore, the statement of Pastuszak et al. (2018) might not be true in our sampling point because they do not show total lake water characteristics. In our data, the average of total phosphorus and total nitrogen in the nearby Vaasa region seems similar to a past analysis by Pitkänen et al. (1986), suggesting a regulated natural habitat has existed in the area for quite some time. The quantity and quality (coastal morphometry, season) and the concentrations in the open sea are the main factors regulating total nutrients in the surface layer of coastal waters (Pitkänen et al., 1986).

One immediate conclusion is that the water quality in all six sampling points is at least at the passable level of the SYKE standard. It is apparent from the summary in Table (Table 1) that water quality at the 3 f sampling point is the worst of the six, and yet it was found that even here the water is above the passable level. It is also clear that rising air temperature is causing an increase in water temperature because they have a strong Pearson's correlation (product-moment correlations). We cannot confirm direct causality relations, but there is a clear influence of increasing air temperature on increasing water temperature, further probably leading to an increase in chlorophyll-a. Plant growth depends on sunshine and temperature. Hence, phytoplankton growth (indicator chlorophyll-a) is influenced by water temperature increase and sun irradiance variations. The time lag found in some analyses shows that expected increases in water temperature and chlorophyll-a levels come sometime (probably days to months of lag) after the air temperature increase. This can be one kind of proof of the influence of air temperature noticed in water quality variables.

Explaining the correlation between water quality and other parameters of the data is shown in Table 2. There were four statistically significant correlations found between Chl-a and other parameters. These parameters include total phosphorus (TP), Secchi depth, month, and turbidity. An additional positive correlation was found between air and water temperature (0.89691, $P < 0.0001$). These correlations do only show the dependency between them, not causality. Hence, water temperature is a water quality that influences most of the other water quality parameters it is easy to see that the air temperature has affected the water quality. Even the path cannot be seen in this paper. Having such a view helps to notice and confirm that air temperature change affects all over the world also in environmentally protected areas and based on our findings only in a few months. It is shown that April and July air temperatures increase statistically significant and the models explain these increments with 12 and 21 % of these months' observed data, respectively (see Table 3). Water temperature for February, March, June and July found statistically significant results.

The correlation analysis between water quality and nearest weather data and within the water quality variables show similar results in nearly all sampling points. Noted exceptions are positive correlations (at the Vav-19 (3e) site) and negative correlations (at the Vav-7 (3d) site) between total phosphorus (TP) and air temperature. Other analysis results seem similar to the pattern of the Et. Kaupa 1 (3f) correlation outcomes. The correlation results obtained at Vaslörgloppet (3c) appear to be untrustworthy because of the limited amount of data gathered by ELY-keskus at this location. All data were not possible to analyse using *t*-test, one-way ANOVA, two-way ANOVA, multi-way ANOVA or ANCOVA due to the fact the data are not normal.

The lack in this study would be not able to use more various methods due to the data being found to be non-normal data. This limits the whole analysis to be based on those analyses that can allow the use of non-normal data. The water system can be affected by various climate change variables including air temperature, precipitation, and snowfall level. One of the limitations of this paper is that only air temperature was considered as an indicator due to a lack of enough data. The importance of air temperature change effect on water quality in this paper investigation is the understanding of what kind of changes can be seen in water systems and this helps how to overcome them through time. Moreover, the significance of the study is showing the effect of air temperature change in the Kvarken Archipelago in a naturally protected area in April and July month. Knowing changes in the weather data and water systems in the Kvarken Archipelago can show how these effects are real even in protected areas and why we must minimize the causes and effects of climate change. This can be done not only by protecting the environment, but also world scale solving climate change causes. As can be seen here even if we protect our local environment, if the world does not work together with the reduced emission sources, these emissions can influence everyone in the world where ever we are. Not only the current generations but the next generations will be affected because of our unfairness towards the environment and its protections.

5. Conclusions

In the preliminary analysis, the summary of statistics showed that the 3 f sampling point is the worst based on comparing it with other sampling points using the mean and standard deviations. This was one of the reasons to choose it as a representative sampling point. It was found that the water quality of sampling point 3 f (the worst) is above the passable level. This and the summary statistics confirm that all sampling water quality statuses based on SYKE standards were at least above the OK level. Showing the protected area was not affected severely by other pollution sources. In dependency analysis, it was found that statistically significant Parsons correlations between Chl-a and (TP, Secchi depth, Month, and turbidity). As well, air temperature shows a statistically significant correlation with water temperature.

Trend analysis shows that there are anomalies in past and future trends. As well, they show that in the future air, water and Chl-a are expected to rise and snow-depth levels to decline. In the main analyses section, the presence of air temperature changes in the months of April ($R2 = 0.2109$ & $P = 0.0009$) and July ($R2 = 0.1207$ & $P = 0.0155$). One explanation to see changes only in April and July months can be because of a shortage in the data collection period. Changes in water quality variables (Chl-a and water temperature) were found in some months. There are strong relationships between air temperature and water quality was shown the relation between air and water temperature.

According to our analysis of large amounts of data, a fairly flat trend (slope = 0.20158) of air temperature increases in the Kvarken Archipelago can be observed for 1974–1994, which is statistically significant. However, this finding explains by this model only 1.81 % of the data. The world's heritage site has been well protected to some level. Still, changes already are visible and have direct effects in this well-reserved area on both the air temperature change vs. year ($\rho < 0.05$) in April and July. Therefore, climate action is an obligation to protect Kvarken Archipelago's species and ecosystems. New policies must focus, be deployed and implement not only on protecting the environment but also on declining and stopping the causes of climate change or air temperature changes. How climate change has affected the ecosystem representation within the Kvarken Archipelago will be our further research topic, including other climate change variables such as precipitation patterns and snowfall levels.

Ethics approval and consent to participate

Not applicable

Consent for publication

All the authors agreed and gave their consent for publication.

CRediT authorship contribution statement

Nebiyu Girgibo – original idea, writing the original manuscript, data gathering, data analysis, reviewing, editing and fund acquisition. Xiaoshu Lü –reviewing, editing, and funding acquisition. Erkki Hiltunen – requesting data, reviewing, editing and funding acquisition. Pekka Peura, and Zhenxue Dai – reviewing and editing.

Funding's

The first author (Nebiyu Girgibo) received doctoral student funding from the University of Vaasa foundation, the Ella and George Foundation and the Finnish Cultural Foundation during conducting the research. Additional salary and cost support were received for Nebiyu Girgibo from the Academy of Finland funding in the Profi 4 project.

Data availability

The data is not available for public use because the research is ongoing, and our research teams would like to continue with this research so we are not willing to share our current data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

There is no conflict of interest.

Acknowledgements

All the experts who participated in the whole research are acknowledged. Funding organizations of the foundation of the University of Vaasa, the Ella and George Foundation and the Finnish Cultural Foundation are acknowledged for doctoral study grants for Nebiyu Girgibo. Additional salary and cost support received for Nebiyu Girgibo from the Academy of Finland funding in the Profi 4 project are acknowledged. The University of Vaasa was also acknowledged for suitable research workmates, resources and employment.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.162599.

References

Ahmed, M., 2019. Medconnection – Finland lifestyle: Water in Finland purest in the world [online]. Cited 17 Jan. 2023. https://mediconnection.fi/en/water-finland-purest-world/.

Arau'jo, M.B., Nogués-Bravo, David, Thuiller, Wilfried, 2011. Climate change threatens European conservation areas. Ecology Letters 14 (2011), 484–492. https://doi.org/10.1111/2Fj.1461-0248.2011.01610.x.

Begge, P., Meriläinen, J.J., 1985. The occurrence of water mites (Acari: Hydrachnellae) in the estuary of the River Kyrönjoki (Bothnian Bay). Annales Zoologici Fennici 22 (2), 123–127. https://www.jstor.org/stable/23734134.

Choo, J.M., Taskinen, J., 2015. Effect of short-term temperature change on cercarial release by Rhipidocotyle fennica (Trematoda, Bucephalidae) from the freshwater bivalve host, Anodonta anatina. Ecological Parasitology and Immunology. 4 6 pp.

Fonsellius, S.H., 1986. The hydrography of the Gulf of Bothnia. Report From the Hydrography Group. 68. Publications of the Water Research Institute, National Board of Waters, Finland.

Girgibo, N., 2021. The effect of climate change on water and environment resources in the Kvarken Archipelago area. 90 pp. 2016 – 2021The University of Vaasa Reports 20. University of Vaasa, Tritonia, library, Vaasa, Finland . http://urn.fi/URN:ISBN:978-952-476-941-9.

Girgibo, N.W., 2022. Seaside renewable energy resources literature review. Climate 10 (10), 153. https://doi.org/10.3390/cli10100153 2022.

Girgibo, N., Mäkiranta, A., Lü, X., Hiltunen, E., 2022a. Statistical investigation of climate change effects on the utilization of the sediment heat energy. Energies 2022 (15), 435. https://doi.org/10.3390/en15020435.

Girgibo, Nebiyu, Lü, Xiaoshu, Hiltunen, Erkki, Peura, Pekka, Tong, Yang, Zhenxue, Dai, 2022b. A conceptual framework for the future of sea-level rise and land uplift changes in the Vaasa region of Finland. SCIREA J. Geosci. 1, 23–57. https://doi.org/10.54647/geosciences17154.

Hietikko-Hautala, T., 2012. The Kvarken Archipelago World Heritage Sites: Echoes of the Ice Age. Central for Economic Development Transport and the Environment for South Ostrobothnia (ELY-Keskus), Vaasa, Finland. ISBN: 978-952-257-095-6, p. 159.

Huttunen, M., et al., 1986. Phytoplankton of the open sea areas of the Gulf of Bothnia – Observations made in the first stage of the Baltic monitoring programme in 1979—1983. Publications 0f the Water Research Institute, National Board of Waters, Finland, No. 68.

Kauppila, P., 2007. Phytoplankton quantity as an indicator of eutrophication in Finnish coastal waters - application within the water framework directive. DissertationMonographs of the Boreal Environment Research 31. Finnish Environmental Institute, Helsinki, Finland 978-952-11-2898-1.

Kernan, M., Battarbee, R.W., Moss, B.R., 2010. Climate Change Impacts on Freshwater Ecosystems. Wiley-Blackwell, Oxford 978-1-4051-7913-3.

Kraemer, B.M., Kakouei, K., Munteanu, C., Thayne, M.W., Adrian, R., 2022. Worldwide moderate-resolution mapping of lake surface chl-a reveals variable responses to global change (1997–2020). PLOS Water 1 (10), e0000051. https://doi.org/10.1371/journal.pwat.0000051.

Kupiainen, K.J., et al., 2019. Climate impact of finnish air pollutants and greenhouse gases using multiple emission metrics. Atmos. Chem. Phys. 19 (7743–7757), 2019. https://doi.org/10.5194/acp-19-7743-2019.

Li, Z., et al., 2022. The influence of increased precipitation and nitrogen deposition on the litter decomposition and soil microbial community structure in a semiarid grassland. Sci. Total Environ. 844 (2022), 157115. https://doi.org/10.1016/j.scitotenv.2022.157115.

Liu, S., Wang, P., 2022. Emerging solute-induced mineralization in Arctic rivers under climate warming. Sci. Total Environ. 851 (2022), 158091. https://doi.org/10.1016/j.scitotenv.2022.158091.

Mäkelä, K., 1986. Variations in dry matter, phosphorus and organic carbon in two Bothnian Bay sediment cores in relation to hydraulic engineering works. Publications of the Water Research Institute, National Board of Waters, Finland, No. 68.

Meerhoff, M.C., et al., 2007. Effects of habitat complexity on community structure and predator avoidance behaviour of littoral zooplankton in temperate versus subtropical shallow lakes. Freshwater Biology 52, 1009–1021. https://doi.org/10.1111/j.1365-2427.2007.01748.x.

Meriläinen, J.J., 1984. Zonation of the macrozoobenthos in the Kyrönjoki estuary in the Bothnian Bay, Finland. Annales Zoologici Fennici 21 (2), 89–104 1984.

Meriläinen, J.J., 1988. Meiobenthos in relation to macrobenthic communities in a low saline, partly acidified estuary, Bothnian Bay, Finland. Annales Zoologici Fennici 25 (4), 277–292 1988.

de Mour, M.E.P., Rocha, L.dos S., Nabout, J.C., 2017. Effects of global climate change on chlorophyll-a concentrations in a tropical aquatic system during a cyanobacterial bloom: a microcosm study. Ambiente & Água - An Interdisciplinary Journal of Applied Science 12 (3). https://doi.org/10.4136/ambi-agua.2014.

Pastuszak, M., et al., 2018. Reduction of nutrient emission from polish territory to the Baltic Sea (1988–2014) confronted with real environmental needs and international requirements. Oceanol. Hydrobiol. Stud. 47 (2). https://doi.org/10.1515/ohs-2018-0015.

Pearl, J., Mackenzie, D., 2018. The Book of Why: The New Science of Cause and Effect. Hachette Book Group, New York, USA 978-0-465-09760-9.

Peura, P., Sevola, P., 1992. Acidification mosaic of small lakes. A study on 81 lakes in the Kvarken, Gulf of Bothnia (Finland and Sweden). Aqua Fennica 22 (2) 153-171 pp.

Pitkänen, H., Niemi, J., Sarkkula, J., Sandman, O., 1986. Phosphorus and nitrogen balance of a coastal bay. Publications of the Water Research Institute, National Board of Waters, Finland, No, p. 68.

Räike, A., Taskinen, A., Knuuttila, S., 2019. Nutrient from Finnish rivers into the Baltic Sea has not decreased despite water protection measures. The royal Swedish academy of science (KUNGL VETENSKAPS AKADEMIEN): Ambio. Springer, pp. 1–15 https://doi.org/10.1007/s13280-019-01217-7.

Saranko, O., et al., 2020. Impacts of town characteristics on the changing urban climate in Vantaa. Sci. Total Environ. 727 (2020), 138471. https://doi.org/10.1016/j.scitotenv.2020.138471.

SYKE, 2003. SYKE (Finnish Environmental Institute) - Water Quality of Lakes, Rivers and Sea areas in Finland in 200 – 2003 [Online]. Cited 27 Aug. 2020Syke. fi. https://www.syke.fi/download/noname/%7B98588B25-E678-4DE2-8006-6CCBACC3F273%7D/30089.

Water-Quality, 2008. Water Quality: A Filed-based Water Quality Testing Program for Middle Schools and High Schools. Manual. Massachusetts Water Resources Authority, Boston, USA.

Wetzel, R.G., 2001. Limnology- Lakes and River Ecosystems. 1006Third edition. Elsevier Science (USA), California, USA ISBN: 0-12-744760-1.

Winder, M., Schindler, D.E., 2005. Climate change uncouples trophic interactions in an aquatic ecosystem. Ecology 85, 2100–2106. https://doi.org/10.1890/04-0151.