



Ecological status classification of marine waters

Indicator development and monitoring requirements

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Nordic Council of Ministers

Store Strandstræde 18
DK-1255 Copenhagen K
Phone (+45) 3396 0200
Fax (+45) 3396 0202

Nordic Council

Store Strandstræde 18
DK-1255 Copenhagen K
Phone (+45) 3396 0400
Fax (+45) 3311 1870

www.norden.org

Contributors:

Jacob Carstensen, National Environmental Research Institute, Århus University
Birger Bjerkeng, Norsk Institutt for Vannforskning (NIVA)
Pirkko Kauppila, Finnish Environment Institute
Aiste Kubiliute, Centre of Marine Research
Bärbel Müller-Karulis, Institute of Aquatic Ecology, University of Latvia
Carl Rolff, Dept. of Systems Ecology, Stockholm University
Aleksander Toompuu, Marine Systems Institute, Tallinn Technical University

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Preface

The present report is the outcome of the EQUAL project, which was financed by the Environment Monitoring and Data group and the Sea and Air Quality group under the Nordic Council of Ministers. There were 7 institutions involved in the project representing 4 Nordic countries (Denmark, Finland, Norway and Sweden) and 3 Baltic countries (Estonia, Latvia, Lithuania). The project began in 2004 and ended in 2007.

The report is concerned with methods for improving the classification of marine ecosystems under the European Water Framework Directive (WFD). WFD is a measure for regulating the discharge of nutrients to the aquatic environment. Pollution sources are to be regulated based on defined ecological status classes for a variety of indicators. WFD was adopted in autumn 2000 and requires that all EU member states and accession countries define quality classes for transitional and coastal waters.

The practical implementation of WFD is, to a large extent, still unclear but it should legally be in effect from 2004 and monitoring should start in 2007. In “Guidance on typology, reference conditions and classification systems for transitional and coastal waters” produced by the COAST working group it is stated that

“It is recognised that this guidance does not give specific advice on setting EQR values and on the statistical issues surrounding classification. It is suggested that this work needs to be taken further.” and “It is likely that Member States with similar types may find that they can use the same classification tools.”

However, the specific development of classification tools is to be developed within the Member states. These classification systems should be based on scientifically sound principles that ensure correct statistical interpretation of monitoring data and moreover, such systems should have a large degree of generality across national borders. In addition, many countries do not have sufficient capacity to develop classification systems. It is therefore important that this problem is solved on a larger scale involving several countries.

Monitoring data in marine waters often reflect large natural, seemingly irregular variations, and it is a challenging task to distinguish between different quality classes in the presence of uncertainty. Particularly, consequences of a misclassification may potentially be that unnecessary investments are made for reducing nutrient inputs or alternatively, no action is taken even if a water body has a bad water quality. The prime focus in a classification procedure is to reduce the random variability of

the indicators, and this can be achieved by means of explanatory variables (e.g. salinity) or by increasing the amount of monitoring data. Estuaries and coastal areas generally reflect large gradients in salinity as well as for water quality indicators. It is clear that disregarding the salinity dependency for ecological quality indicators will lead to an inadequate implementation of the WFD. Moreover, disregarding the salinity dependency may result in an inappropriate selection of monitoring stations to represent transitional and coastal waters. Other explanatory variables that can reduce the uncertainty of indicators include freshwater discharge, solar radiation, wind speed and direction.

The objective of this report is to describe methods for reducing the random variation by including explanatory variable to account for systematic variation, to show how classification is carried out using a standard set of models that improve the precision of indicators, and to document consequences for monitoring requirements.

This report is a first step towards improving the statistical treatment of marine monitoring data for classification, and the methods presented can be refined further. It is therefore the hope of the authors that this report will raise awareness about the importance of the statistical methods employed in classification, and stimulate further developments in this direction.

Summary

The aim of the European Water Framework Directive (WFD) is to ensure sustainable management of groundwater, freshwater and marine waters in the European Union, in order to obtain good ecological quality of all such water bodies will be obtained by 2015. Water bodies shall be classified according to their ecological status in five quality classes (high, good, moderate, poor, and bad) from a prioritised list of 1) biological elements, 2) chemical and physico-chemical elements, and 3) hydromorphological elements. The biological elements include phytoplankton, other aquatic flora, benthic invertebrates as well as fish. Chemical and physico-chemical elements include water transparency, salinity, temperature, nutrients, oxygen and specific pollutants. Hydromorphological elements include depth variation, sediment, wave, tidal, and flow characteristics. Monitoring networks for classifying water bodies shall be operational by December 2006.

Monitoring data characterising the biological and physico-chemical elements underlie large sources of uncertainty. The confidence of classification shall include sampling and analytical errors, and consequently it is important to partition the total variation into sampling/analytical variation and all other sources. Variations in data that can be accounted for by e.g. seasonal variation or external variables such as salinity, wind, etc. improve precision (reducing the magnitude of random variation) of ecological indicators and reduce their bias (removing effect of non-representative monitoring conditions). In this report 7 areas representing 4 Nordic countries and 3 Baltic countries were analysed (Oslo Fjord, Askö, Laajalahti and Vanhankaupunginlahti Bay, Moonsund, Gulf of Riga, Curonian Lagoon, and Limfjorden). Main emphasis was on the biological element phytoplankton biomass, measured as chlorophyll a, and the supporting chemical and physico-chemical elements water transparency, total nitrogen and total phosphorus. Statistical models that described seasonal variation and variation attributable to the specific sampling conditions were developed specifically to each area. Accounting for seasonal variation in monitoring data was the most important factor for improving precision and reducing bias, but salinity and wind conditions were also found to have a significant effect on the observations. Caution should be exercised when employing statistical models to describe variations in data, particularly in situations with relatively few observations, in order to avoid overfitting and thereby obtaining a too low estimate for the random variation. The random variation (standard error) was generally reduced by about 20% from the covariation analyses conducted on the case

studies in this report, whereas indicator estimates typically changed 10–20% when adjusting for variations in sampling conditions.

A consequence of indicator bias is misclassification whereas poor indicator precision results in lack of confidence for the classification. Three approaches have been devised for classification of indicators taking uncertainty into account in the Common Implementation Strategy (CIS) guidelines. In the fail-safe approach polluters have to bear the burden of uncertainty, whereas in the benefit-of-doubt approach the environment has to bear this burden. In the face-value approach the uncertainty is equally shared between polluters and environment. Rather different classifications can result when indicator uncertainty is large. In this report the statistical principles for classification have been outlined. It is recommended to use 95% confidence levels for classification.

Appropriate number of samples in monitoring programs can be determined knowing the magnitude of the random variation, if permissible deviations from the boundaries used for classification are specified such that if the true mean value deviates more than specified a correct classification should be obtained with a probability (power) of at least 80%. The required number of samples increases with the square of the random variation. Thus, it is crucial to account for systematic variation in the monitoring data. For the 7 analysed case studies large variations in the required number of samples (from ~10 up to 1000) were obtained due to differences in the magnitude of the random variation, but also the permissible deviation from boundaries used in classification is a crucial parameter for the design of monitoring networks. It is therefore of paramount importance that guidelines towards the concrete implementation of WFD classification are determined on a pan-European level. This report contributes technical support for making such decisions.

1. Indicators of ecological status

The EU Water Framework Directive (WFD) introduces a classification approach to water quality assessment. Based on a set of indicators for various quality elements, water bodies will be classified into five predefined classes. Failure to meet “good” ecological status will require the initiation of management plans to ensure improvement of water quality. The EQUAL project has developed a framework for indicator classification that takes the inherent stochastic nature of monitoring data into account. Emphasis is put on indicators that describe the physico-chemical and biological quality elements in the WFD.

This chapter describes the legal requirements for water quality monitoring in the seven countries involved in the EQUAL project, which are determined by the WFD as well as the HELCOM and OSPAR conventions and lists the indicators currently used for marine coastal monitoring. Implementation of the WFD in the project area is analyzed and attempts to harmonize monitoring under the regional conventions (HELCOM, OSPAR) with WFD requirements are described. Further, the EU Commission has proposed a Marine Strategy Directive, which is currently under negotiation. The impact of the planned directive on the monitoring requirements in the case study areas covered by EQUAL is therefore not clear yet.

1.1 WFD requirements for transitional and coastal water monitoring

The Water Framework Directive provides a framework for the protection of ground water, inland surface waters, transitional waters (estuaries) and coastal waters. The overall aim of the WFD is (1) to prevent further deterioration, protect and enhance the environmental status of aquatic systems, and (2) to promote the sustainable use of water, while progressively reducing or eliminating discharges, losses and emissions of pollutants and other pressures for the long-term protection and enhancement of the aquatic environment. The WFD provides national and local authorities with a legislative basis for the maintenance and recovery of water quality to achieve good ecological and chemical status for all surface waters and good chemical status for groundwater. Accordingly, the WFD is considered to be the most significant piece of legislation regarding water policy produced in the last 20 years.

The coastal waters covered by the WFD are limited to the surface water on the landward side of a line, which is one nautical mile on the seaward side from the nearest point of the baseline from which the breadth of territorial waters is measured. Open marine waters are not covered, but the WFD is likely to influence management of all marine ecosystems because all land-based inputs of pollutants will pass through the coastal zone to the open waters. The WFD further requires EU Member States to develop classification systems to describe the ecological status of a given water body at a given time.

Member States shall also monitor and assess the ecological status of coastal waters. The monitoring activities shall in principle cover ecological status and chemical status, cf. Annex V of the WFD. The requirements with respect to monitoring of eutrophication in coastal waters are:

- Monitoring networks shall be established in accordance with the requirements of Article 8 of the Directive¹.
- Monitoring shall take place in the coastal waters downstream of each river basin (catchment area).
- Monitoring shall permit classification of water bodies in five classes consistent with the normative definitions of ecological status.
- Monitoring networks shall include both surveillance monitoring and operational monitoring.
- In some cases monitoring networks should include investigative monitoring.
- Monitoring networks shall be based on variables/indications which are indicative of the status of each relevant quality element:
 - Biological
 - phytoplankton
 - other aquatic flora
 - macro invertebrates
 - fish fauna (in transitional waters)
 - Hydromorphological
 - morphology
 - dominating currents
 - advection from adjacent coastal waters
 - Physico-chemical
 - temperature
 - oxygen concentrations
 - salinity
 - nutrient status

¹ Article 8 stipulates: 1) Member States shall ensure the establishment of monitoring networks in order to establish a coherent and comprehensive overview of ecological and chemical status and ecological potential, 2) networks shall be operational by 1st January 2007 at the latest and 3) technical specifications and standard methods for analysis and monitoring shall be documented.

- Monitoring of biological quality elements shall be done at the appropriate taxonomic level in order to achieve adequate confidence and precision in the classification of the quality elements.
- Estimates of level of confidence and precision of the results provided by the monitoring plans shall be given in the programs of measures taken in order to achieve the environmental objectives.

The monitoring activities can be one of three types: 1) surveillance monitoring, 2) operational monitoring and 3) investigative monitoring. The following text describes the objectives of each type of monitoring.

Surveillance monitoring: The objective of surveillance monitoring is to provide information for:

- supplementing and validating the assessment procedure cf. Annex II of the WFD,
- design of future monitoring activities,
- assessment of long-term changes in natural conditions,
- assessment of long-term changes resulting from human activities.

In practice, surveillance monitoring shall be carried out in areas where the ecological status has been established to be either high or good.

Operational monitoring: The objective of operational monitoring is to:

- establish the status of those water bodies identified as being at risk of failing to meet their ecological objectives, and
- assess any change in the status of such water bodies.

The directive specifies a suite of criteria for selection of both abovementioned objectives. Monitoring frequencies given in Annex V of WFD should apply for surveillance monitoring, whereas monitoring frequencies under operational monitoring should be sufficient to provide reliable status assessment.

Investigative monitoring: The WFD requires investigative monitoring to be carried out:

- in areas where reasons for not fulfilling ecological objectives are unknown,
- in areas where the ecological objectives are not likely to be met and operational monitoring has not already been established,
- to ascertain the magnitude and impacts of accidental pollution.

1.2 Water quality monitoring in HELCOM and OSPAR areas

1.2.1 HELCOM

Attempts to jointly manage the pollution of the Baltic Sea with nutrients and toxic substances date back to 1974, when the Baltic Coastal states signed the Helsinki Convention and established its administrating agency, the Helsinki Commission (HELCOM). The Helsinki convention was revised in 1992 and ratified by all bordering countries and the European Union in 2000. The Helsinki Convention now covers the entire Baltic Sea, including also the drainage area.

HELCOM harmonized the different national efforts of the Baltic Sea monitoring in its COMBINE monitoring program established in 1992. COMBINE (Cooperative Monitoring in the Baltic Sea Environment) aims to ensure continuous international monitoring of the amounts and effects of nutrients and contaminant in the Baltic Sea ecosystem. COMBINE includes a network of common monitoring stations and a set of mandatory core variables and supplementary main variables (see also Table 2). COMBINE parameters cover hydrographic conditions, nutrient concentrations, and biomass of lower trophic levels (phytoplankton, phyto-benthos, zooplankton, and macrozoobenthos). COMBINE also sets minimum requirements for the monitoring frequency, spanning from yearly for mapping stations for winter nutrient concentration and macro-zoobenthos, to weekly for high frequency stations following the seasonal succession of nutrients and phytoplankton during the vegetation period. Traditionally, HELCOM COMBINE has focused on open sea monitoring, including only few stations in the coastal zone. Of the 412 monitoring stations committed by the contracting parties in 2005, 91% were located in waters deeper then 10 m, and 82% at depths larger then 15 m (based on Annex C1 of the HELCOM COMBINE manual, (www.helcom.fi/Monas/CombineManual2)), but the number of coastal monitoring stations in national monitoring programs is often larger than the number of stations committed and reported to the COMBINE program.

With the fourth periodic assessment (HELCOM 2001; HELCOM 2002) and a description of the ecosystem status in 1999–2002 (HELCOM 2003), HELCOM concluded the series of regular joint overall assessments of the environment of the Baltic Sea area and instead introduced a series of indicator reports, which will be support thematic assessments to achieve more focused and timely delivery of information. Indicator reports follow the development of important parameters, e.g. water exchange with the North Sea, oxygenation conditions, freshwater input, atmospheric inputs, phytoplankton concentrations, over longer time-periods. Further, HELCOM aimed to introduce Ecological Quality Objectives (EcoQO) as a management tool. Ecological Quality Objectives are

defined conditions, which should be achieved by Baltic Sea management, and which indicate whether “good quality status”, as for example demanded in the Water Framework Directive, is met in the Baltic Sea. HELCOM adopted the use of Ecological Quality Objectives (EcoQO) in the 2003 Bremen declaration and also conducted a pilot study drafting a system of Ecological Quality Objectives (Poutanen et al., 2003). Presently, a subset of the proposed EcoQOs are, as Ecological Objectives, the central elements in the HELCOM Baltic Sea Action Plan (HELCOM 2006), which is currently under negotiation by the contracting parties.

The thematic assessment of eutrophication is presently carried out within the HELCOM EUTRO-PRO project. Within EUTRO-PRO, the contracting parties will jointly assess the eutrophication status in the Baltic Sea by 2009. Nutrients, water transparency, phytoplankton (including algal blooms), submerged aquatic vegetation, oxygen concentration, and invertebrate benthic fauna will be the central elements in the assessment. For each indicator, reference conditions and a permissible deviation from reference status will be used to classify the eutrophication status of Baltic Sea sub areas. The planned thematic assessment will therefore achieve the transition from a description of eutrophication status to an evaluation approach in terms of quality classes, which are, even though mainly targeted towards open waters, largely consistent with the normative definitions of the Water Framework Directive.

1.2.2 OSPAR

Within OSPAR a so called Common Procedure for the assessment of eutrophication status has been developed. In principle, the procedure distinguishes between ‘problem areas’ and ‘non-problem areas’ with respect to eutrophication. However, some contracting parties have identified so-called ‘potential problem areas’, and for this purpose a ‘comprehensive procedure’ has been developed in order to clarify if these areas are ‘problem areas’ or not.

The procedures are straightforward. The starting points are reference conditions or background conditions. The acceptable deviation from these has tentatively been set at 50% or less, if justified. Only Denmark has opted for less (25% due to the sensitivity of the permanently stratified open waters or due the high residence times of the estuaries).

The indicators of eutrophication in relation to the Common Procedure are:

- 1: Degree of nutrient enrichment (causative factor)
 - Riverine total N and total P inputs and direct discharges
 - DIN and DIP concentrations
 - Winter N/P ratio (compared to Redfield-ratio = 16)
- 2: Direct effects of nutrient enrichment

- Chlorophyll a concentration
- Species composition of phytoplankton (region or area specific)
- Macrophytes (region specific)

3: Indirect effects of nutrient enrichment

- Oxygen concentrations (hypoxia/anoxia)
- Zoobenthos (changes in species composition and kills)
- Carbon contents in sediments
- Algal toxins (DSP/PSP)

Based on monitoring data, assessments of the eutrophication status of the different basins or water bodies are carried out for the above mentioned categories. It is noteworthy that the OSPAR procedure is based on a ‘one out – all out’ principle, being almost similar to the WFD principles (Table 1.1).

Table 1.1: Integration of categorized assessment criteria (combination matrix).
‘+’ = eutrophication effects, ‘-’ = no eutrophication effects.

Area	Causative factors	Direct effects	Indirect effects	Classification
A	+	+	+	+
	+	+	-	+
	+	-	+	+
B	-	+	+	+
	-	+	-	+
	-	-	+	+
C	-	-	-	-

1.3 Harmonization of monitoring programs between WFD, HELCOM and OSPAR

Attempts to harmonize monitoring programs between Water Framework Directive, HELCOM and OSPAR are driven by the need to design cost-efficient, consistent observation networks, as well as by the wish to create a consistent European assessment of marine water quality, integrating both coastal and open waters. A unified assessment of European marine water quality is the main objective of the EU Marine Strategy, which is currently under preparation. Harmonization efforts between the regional conventions and the WFD also serve to prepare the design of the EU Marine Strategy. For example, HELCOM, OSPAR, the Black Sea Commission, and the EU Joint Research Center have elaborated a pan-European framework for eutrophication assessment at workshops in Istanbul in 2004 and 2005, which provides a unified framework for addressing the cause and effect relationships in marine eutrophication.

1.3.1 Classification scheme

The WFD defines the overall goals of monitoring, which should permit the classification of each water body into the predefined water quality classes “high”, “good”, “moderate”, “poor”, and “bad”, as well as provide information on the causes of water bodies failing to meet good water quality (Common Implementation Strategy, 2003). Water quality classification is therefore a central element of the WFD. Also OSPAR uses a classification approach, whereas HELCOM is only in the stage of developing EcoQOs as a classification tool. Within OSPAR, work to coordinate the Common Procedure with the WFD has been initiated. So far, focus has been on principles in relation to management goals. For example, there is a common understanding that the border (= the management standard) between good and moderate ecological status *sensu* the WFD is equivalent to the border between problem and non-problem areas *sensu* the OSPAR Common procedure.

1.3.2 Indicators and parameter

Monitoring parameters and indicators utilized in the different programs relevant for the EQUAL study area – the EU Water Framework Directive, HELCOM COMBINE monitoring, HELCOM indicator reports, suggestions for HELCOM EcoQOs, OSPAR requirements, and the European Environmental Agency (EEA) indicator reports – partially overlap (Table 1.2). All programs apply a combination of parameters and indicators that characterize hydrographic conditions, nutrient concentrations, and the lower part of the marine foodweb, including phytoplankton and phytobenthos, macrozoobenthos and in some cases also zooplankton and coastal fishes. In principal, both OSPAR and HELCOM monitoring activities are focused on open water and not as much on coastal waters. OSPAR monitoring of open water is to a large extent based on measurements of physico-chemical parameters (temperature, salinity, nutrients) and benthic macro-invertebrates. These parameters – or quality elements – are also included in the WFD and in HELCOM COMBINE.

Recent attempts to harmonize the indicator systems currently in use or proposed for monitoring in the HELCOM and OSPAR areas among each other and with the WFD have led to a number of developments. HELCOM in 2003 has launched the MONPRO project, which aims to harmonize HELCOM monitoring with the requirements of the Water Framework Directive.

Neither Water Framework Directive nor the convention-wide monitoring programs (HELCOM COMBINE, OSPAR JAMP/CEMP) define a rigorous set of indicators for water quality assessment. According to Annex V of the WFD, monitoring activities must cover biological and physicochemical quality elements, but the selection of actual indicators for the

respective quality elements is left to the member states implementing the directive.

Table 1.2: Indicators currently used for monitoring and assessment in the Baltic Sea and OSPAR area (adapted from HELCOM MONAS 6, 2003), toxic substances not included (1 = mandatory, 2 = voluntary).

Variable/Substance	EU WFD	HELCOM COMBINE	HELCOM Indicator reports	HELCOM EcoQO project ¹	OSPAR	EEA indicator reports ²
Hydromorphology						
Substrate quantity and structure	1				2	
Hydrography						
Temperature	1	1	*		1	
Salinity	1	1	*		1	
Oxygenation conditions	Oxygenation	1	*	*	1	Oxygen in bottom layer
H ₂ S	Oxygenation conditions	1	*	*	2	
pH		2			1	
Alkalinity		2			1	
Transparency	1	1		*	1	
Nutrients						
NO ₃ + NO ₂	Nutrient conditions	1		Nutrient conditions	1	*
NH ₄	Nutrient conditions	1		Nutrient conditions	1	
Tot-N	Nutrient conditions	1		Nutrient conditions	1	
PO ₄	Nutrient conditions	1		Nutrient conditions	1	*
Tot-P	Nutrient conditions	1		Nutrient conditions	1	
SiO ₄		1		Nutrient conditions	1	
Biology						
Phytoplankton	Abundance, composition, biomass	Abundance, composition, biomass	*	Proportion of siliceous species, harmful algal blooms		Harmful species
Chlorophyll a		1	*	*	1	*
Primary production		2				
Zooplankton		2				
Macrozoobenthos	Composition and abundance of benthic invertebrate fauna	Abundance, composition, biomass			1	
Phytobenthos	Composition and abundance of other aquatic flora	2			2	
Fish	Transitional waters	2				*
Non-indigenous species						*

¹ Poutanen et al. (2003)

² Nixon et al. (2003)

Instead, HELCOM COMBINE and OSPAR JAMP/CEMP monitoring programs define a mandatory set of parameters, together with standard

measurement methods. Aim of the monitoring is not a classification of ecological status, but to quantify the anthropogenic impact on the ecosystem. In the assessment reports monitoring data are often presented in a selective or aggregated way, forming de facto an indicator system to follow long-term ecosystem changes. The indicators used describe hydrographic conditions, nutrient concentrations, as well as phytoplankton, zooplankton, phytobenthos and zoobenthos communities. Therefore, they overlap with physico-chemical and biological quality elements required by the WFD.

1.3.3 Indicators describing physico-chemical quality elements

Salinity and thermal conditions

Assessments by the regional conventions (HELCOM 4th periodic assessment, OSPAR QSR 2000, OSPAR Common Procedure) contain descriptions of salinity, temperature regime and oxygen conditions, which are mainly focused on the open sea. For example, HELCOM (2002) describe temperature and salinity conditions by monthly or annual averages, either for representative stations or as basin wide averages. Also surface (0 – 10 m) and bottom temperature/salinity as well as pycnocline depth (depth of the maximum density gradient) and stratification intensity (buoyancy frequency) have been used. Special emphasis has been put on the water exchange in the North Sea, which determines both the salinity regime as well as bottom water oxygen conditions in the Baltic Sea.

Oxygenation conditions

Also most indicators describing oxygenation conditions in OSPAR and HELCOM assessments are focused on the open sea. HELCOM (2002) characterize oxygen conditions in the Baltic Sea by monthly mean concentrations of H_2S/O_2 in the deep basins, the annual maximum extend of hypoxic areas in the Baltic Proper, and monthly averages of oxygen concentrations in the near bottom layer of representative stations. The European Environment Agency (EEA) has taken a similar approach, describing oxygen conditions by the percentage of stations within a basin, where oxygen concentrations below 2 mg l^{-1} were reported (Nixon et al., 2003). Coastal oxygenation conditions have mainly received attention, when extreme events occurred. For example, after the 2002 anoxic events in the Kattegat, HELCOM produced a dedicated thematic report (Ærtebjerg et al., 2003) describing seasonal dynamics of oxygen concentrations, as well as area and volume affected by low oxygen conditions.

Nutrient conditions

Nutrient levels in the Baltic Sea were evaluated in both HELCOM (2002) and the EEA indicator report (Nixon et al., 2003) according to winter (February) phosphate and nitrate concentrations in the surface (0–10 m)

layer, including a comparison of N:P ratios with Redfield values. Winter nutrient concentrations in the surface layer are also suggested by the HELCOM EcoQO project as a potential indicator (Poutanen et al., 2003), while the WFD only demands the assessments of nutrient conditions, without specifying time period and type of nutrient. To show the seasonal dynamics of nutrient concentrations, HELCOM (2002) presented also monthly mean values in the surface layer. Bottom water processes were analyzed according to nutrient time series in the near bottom layer, linking concentrations changes to stagnation and inflow processes. The OSPAR Common Procedure includes winter nutrient concentrations and N/P-ratio as assessment indicators.

Transparency

The WFD demands to assess the transparency of coastal waters. Also the HELCOM EcoQO project suggests using Secchi depth as an indicator of water transparency (Poutanen et al., 2003). Secchi depth is one of the oldest indicators in the Baltic Sea area with a large number of available measurements, dating back at least to 1902 (Aarup, 2002). However, in HELCOM (2002) only general trends in Secchi depth, referring to time periods of several decades, are mentioned and no data are presented. Secchi depth seems therefore to be more applicable for showing changes over very long time periods, as they are presented, e.g. in the current HELCOM indicator fact sheets (www.helcom.fi/environment2/ifs/ifs2005/en_GB/transparency).

1.3.4 Indicators describing biological quality elements

Invertebrate fauna

Macrozoobenthos abundance and species composition, potentially also lumped into species groups, are the parameters required by WFD monitoring of benthic fauna (Common Implementation Strategy, 2003). Abundance and species composition are also suggested in the HELCOM EcoQO project. Due to the slow changes in macrozoobenthos communities, all data in HELCOM (2002) are presented as annual values. Abundance, number of species, and biomass aggregated into taxonomic groups or functional groups (herbivore, detritivores, filter feeders) were used as indicators. A more recent indicator fact sheet, using mainly time trends in individual species, is presented on the HELCOM website (www.helcom.fi/environment2/ifs/ifs2005/benthos_folder/en_GB/benthos)

Angiosperms and macroalgae

With respect to benthic flora, the WFD requests to monitor phytobenthos – angiosperms and macroalgae – species composition and abundance. The implementation guidelines emphasize, that also mapping at various scales to document extend and distribution of phytobenthos provides

important indicators. HELCOM (2002) reports the depth distribution or total biomass of phytobenthos, phytobenthos species composition, phytobenthos coverage, as well as the upper and lower depth limit of individual species and species belts (*Fucus vesiculosus*, *Zostera marina*). Also the extent and thickness of drifting filamentous algal mats were described. Along these lines, also the HELCOM EcoQO project suggests to use the distribution of sensitive communities (*Fucus vesiculosus*) and the occurrence of macroalgae mats as indicators.

The OSPAR Common Procedure used macrophytes as an assessment indicator. Depth distribution of eelgrass and density (% coverage) of macroalgae at different depths has been applied for Danish waters.

Phytoplankton

A variety of phytoplankton indicators are currently used in the HELCOM/OSPAR areas. The guidance documents to the WFD (e.g. Common Implementation Strategy, 2003) suggest using abundance, species composition, diversity and biomass as indicators. Within the HELCOM assessments, data are mainly reported according to important taxonomic classes (diatoms, dinoflagellates, cyanobacteria, sometimes also nanoflagellates), rarely according to the abundance or biomass of individual species. Seasonal dynamics are generally divided into spring, summer, and autumn periods. The HELCOM EcoQO project suggests using the proportion of siliceous species as a simple species composition indicator. The implementation documents to the WFD, however, recommend focusing on algal blooms by using bloom frequency and intensity as potential phytoplankton indicators.

WFD guidance documents, HELCOM assessments and indicator reports, as well as the EcoQO project give special attention to nuisance or harmful algal blooms. These are for example described in HELCOM (2002) by the occurrence of high phytoplankton biomass in summer, occurrence of N-fixing cyanobacteria, presence of toxic species, exceptional water color, or occurrence of surface accumulations. EEA (Nixon et al., 2003) used occurrence of shellfish poisoning as a harmful algal bloom indicator.

The OSPAR Common Procedure includes maximum and mean chlorophyll *a* concentrations and changes in species compositions as assessment indicators. Chlorophyll *a* as a simple phytoplankton biomass indicator has also been used in the HELCOM assessments, for example as seasonal average concentrations, or as changes in summer concentrations as seen by SeaWiFS satellite images (www.helcom.fi/environment/indicators2003/jrc_chloro2003_map.html). The WFD does not explicitly mention chlorophyll *a* as an indicator for phytoplankton biomass, but it is extensively discussed in the guidance documents (e.g. Common Implementation Strategy, 2003).

1.3.5 Indicators not included into WFD

Zooplankton

Macrozooplankton links primary producers in marine ecosystems to the higher trophic levels. Despite its ecological importance, zooplankton is neither included in the WFD list of biological quality elements nor in the HELCOM EcoQO proposal. Zooplankton is not used in relation to the OSPAR Common Procedure, but the HELCOM assessment describes annual averages of zooplankton abundance or biomass for all subbasins, aggregating species mostly into subdivisions.

1.4 Implementation of WFD and HELCOM/OSPAR requirements into national water quality monitoring programs

1.4.1 Norway

The OSPAR Common Procedure has been applied to the coast of Southern Norway by the Norwegian Institute for Water Research (NIVA) on contract with the Norwegian State Pollution Control Authority (SFT).

- The Comprehensive Procedure was applied to the coastal water of the Norwegian Skagerrak coast (Molvær et al. 2003a), with the inshore waters divided into 44 sub-areas. The classification was based on the existing Norwegian Classification System (NCS) for nutrients, chlorophyll *a*, oxygen and soft-bottom fauna. Otherwise the OSPAR criterion was used. For many areas the classification is uncertain due to lack of observations (no data, data too old, or data not spatially representative). The general approach was to classify such areas as Potential Problem Areas.
- The OSPAR Screening Procedure was applied to the coastal water of the Norwegian west coast (Molvær et al. 2003b). There are relatively few observations along the coast, so assessment of large areas was based on expert judgment of pressure and water exchange. Of 106 areas, 46 were classified as Non Problem Areas (NPA) (Low anthropogenic nutrient load, mainly high and unrestricted water exchange). For the other areas, it was recommended to apply the Comprehensive Procedure for a final classification.

The Norwegian Classification System (NCS) was developed in 1993–94 by NIVA on contract with SFT, to guide local environmental management. The system comprised water quality, metals and organic micro-pollutants in sediments and biota, soft bottom fauna and suitability for various uses of marine water. A revised version was presented in 1997.

There are 5 eutrophication classes, with criteria defined for summer averages of surface chlorophyll *a* and secchi depth, summer and winter averages for surface nutrients, and deep water oxygen minimum. For surface waters there are two sets of limiting values, for high-saline waters and for salinities below 20.

For the implementation of the Water Framework Directive in Norway, the Norwegian Institute of Water Research (NIVA) and the Norwegian Institute of Nature Research (NINA) are currently conducting a study to develop the scientific foundation for a new classification system where status class is assessed by measuring the degree of deviation from reference conditions for different biological and physico-chemical elements. The work is organized as a strategic institute program, BIOKLASS, funded by the Norwegian Research Council from 2003–2006. The results so far are presented in a recent report (Solheim et al. 2004). For marine waters, the report proposes criteria, mainly as various species indices, and possible boundary values for macroalgae and benthic fauna on soft bottom sediment. The results are still tentative and uncertain. They will be used as input to the international intercalibration process comparing assessment systems across different European countries, as well as to the EU research project REBECCA (Relationships between ecological and chemical status of surface waters), and are expected to be revised in this process.

The focus is on defining criteria for the good/moderate boundary for the most sensitive biological elements and most common pressures. This boundary will be used to separate water bodies at risk of not obtaining the objective of good status from those not at risk. The results of this risk assessment are to be reported to ESA in March 2005 (WFD Article 5 report).

1.4.2 Denmark

The monitoring requirements of the EU WFD, HELCOM COMBINE, OSPAR JAMP as well as a number of other EC/EU directives (Nitrates Directive, Habitat and Species Directive, Urban Waste Water Directive, Dangerous Substances Directive) have been implemented via the national water monitoring program NOVANA for the period 2004–2009.

NOVANA covers: 1) eutrophication (incl. hydrography), 2) contaminants, and 3) bio-diversity and marine protected areas (MPAs). Hydrodynamical modeling of both open water and coastal water/estuaries (retention) is integrated.

In the NOVANA program, the following indicators are monitored:

Physical-chemical measurements in the water column:	• Profile measurements (pressure, temperature, conductivity, light attenuation and fluorescence) • Nutrients (total N, nitrite+nitrate, ammonium, total P, orthophosphate P, inorganic silica, chlorophyll a) • Oxygen concentration • Secchi-depth
Plankton:	• Phytoplankton (species, abundance and biomass) • Primary production • Micro- and mesozooplankton (species, abundance and biomass)
Submerged aquatic vegetation:	• Macroalgae (species, abundance) • Eelgrass (distribution and depth limit) • Geographical coverage incl. shoot density and biomass
Benthic macrofauna:	• Species, abundance and biomass • Biomass of filtering benthic animals (mussels)
Sediments:	• Internal loading (nitrite+nitrate, ammonium, orthophosphate, oxygen) • Pigments (chlorophyll a)

In addition to the above list, coastal fish populations are monitored in 7 areas.

All monitoring data are in principle public domain and thus available via the internet. Monitoring data can be downloaded at <http://mads.dmu.dk>. Technical guidelines, data formats, deadlines for data submission, quality assurance procedure as well as reporting guidelines are well documented.

NOVANA is reported annually, both by local authorities and as a national state-of-the-marine-environment report. Data are subsequently submitted to relevant international organizations (ICES, HELCOM OSPAR, EEA). Further information can be found at <http://m-fdc.dmu.dk>.

1.4.3 Sweden

In Sweden the HELCOM/OSPAR requirements for monitoring are included in the national programs by application of the standardized methods recommended by the HELCOM and OSPAR organizations. The Swedish national marine monitoring programs presently contain the following components: Soft bottom macrofauna (species composition, abundance and biomass), vegetation covered bottoms (species composition, coverage and biomass), pelagic monitoring (temperature, salinity etc., nutrients, phytoplankton and zooplankton), coastal fish populations (species composition, abundance, health status and pollution load), health status of stationary fish populations, health status of marine top consumers (seal and sea eagle), metals and organic pollutants in marine biota (concentrations in fish, guillemot eggs and blue mussels), embryonal development of amphipods (toxicological effects) and swimming water quality (algal and bacteriological information). More detailed information

on the programs can be found on the home page of the Swedish EPA (<http://www.naturvardsverket.se/>).

WFD has not yet had a direct effect on the design of the national Swedish monitoring programs. Five districts have been identified for the administration of the WFD with a new water authority in each. The five districts are the Bothnian Bay, Bothnian Sea, Northern Baltic Proper, Southern Baltic Proper and the Western Sea (Kattegat & Skagerrak). The coastal waters will further be organized in 23 type areas mainly according to salinity, water exchange, stratification and wave exposure. In some areas effects of ice coverage, depth and bottom substrate will also be used for the typology. Work with development of water quality estimators for each monitoring activity has been initiated. For each type area, site-specific levels of the quality estimators will be identified to estimate the environmental status of the area in accordance with the five level scale of the WFD.

1.4.4 Finland

Assessment of the trophic status in Finland's coastal waters is based on a comprehensive monitoring network with ca. 1000 sampling stations. The Finnish Institute of Marine Research (FIMR) via their ca. 50 stations performs the monitoring in the open sea. The national monitoring of coastal water quality is carried out by the Finnish Environment Administration (FEA), which altogether has ca. 100 sampling stations. Thirteen of the stations of FEA and some of the FIMR are monitored intensively. The network of local monitoring covers most of the sampling stations. The variables include hydrography and water chemistry as well as amounts of phytoplankton and zoobenthos. The spatial and temporal coverage of biological monitoring is, however, less than the chemical monitoring. As a whole, the network is a good basis for the implementation of the Water Framework Directive (WFD).

The national coastal typology according to the WFD comprises 11 types around Finland, which have also been tested by biological data. The assessment of the effects of human disturbance and sensitivity of surface waters is in a draft stage. Developing of classification and identification of indicators for phytoplankton, macrophytes and zoobenthos are going on both on the national and international level through EU projects such as CHARM and REBECCA. Implementation of monitoring according to the WFD in Finland has been started by a EU Pilot project in the River Oulujoki basin, which aims at testing the inland and coastal monitoring network.

The national monitoring programs, carried out both in the open sea by FIMR and in the coastal waters by FEA are a part of the international Baltic Monitoring Programs of the Helsinki Commission (HELCOM). The monitoring results are reported annually to the database of HELCOM, which is maintained by the International Council of the Explora-

tion of the Sea (ICES). Finland has taken part in the reporting of HELCOM, e.g. in the periodic assessments of the state of the Baltic Sea. At present, the monitoring programs of HELCOM are in a stage of changes, as the WFD has set new challenges also to international Baltic monitoring. This will bring changes in the national coastal monitoring programs of Finland as well.

1.4.5 Estonia

Prior to 1998 the Estonian National Programme for Sea Monitoring accounted primarily for the requirements of the Baltic Sea Monitoring Programme (BMP) of HELCOM. The programme was aimed at preserving the continuity of the monitoring activities carried out by the Hydrological and Meteorological Service in the earlier years. It was divided into two parts: one dealt with eutrophication of the marine environment and the related problems (Sub-programme “Eutrophication”) and the other with problems related to the pollution of the marine environment with oil products, phenols, heavy metals and toxic substances (Sub-programme “Dangerous Substances”). In 1995, a third sub-programme “Monitoring of Biota of the Coastal Sea” was added to the National Programme. Due to lack of financing, only one part of the latter sub-programme, “Phyto-benthos”, has been implemented. Since 1998, when the new Baltic Sea Monitoring Programme COMBINE, which includes monitoring of the open sea as well as of the coastal sea, was approved, the major part of the Estonian National Programme for Sea Monitoring has been incorporated into the international information exchange carried out via HELCOM. Now, according to the directive of the Estonian government and in compliance with the WFD, the Estonian territory as a part of the Baltic Sea drainage area forms an integral drainage area divided into nine subareas.

The general objective of Estonian marine monitoring is to determine the impact of human activities on the environment and biota of the Baltic Sea, and to determine the range of influence of these activities in the context of natural changes, including qualitative and quantitative assessment of the effectiveness of the measures applied.

1.4.6 Latvia

Latvia is a HELCOM contracting party and the marine monitoring program is designed according to the principles of the HELCOM COMBINE program. The national monitoring network consists of a total of 69 stations. For monitoring eutrophication and its effects, the measurement program includes hydrographic parameters (salinity, temperature, oxygen/hydrogen sulfide, pH), nutrients (NO_3 , NO_2 , NH_4 , total nitrogen, PO_4 , total phosphorus, SiO_4) and biological variables (chlorophyll *a*, phytoplankton biomass/species composition, mesozooplankton biomass/species composition, macrozoobenthos biomass/species composition), and bacte-

rioplankton. In the Gulf of Riga, monitoring frequency is designed to follow the seasonal dynamics of the marine ecosystem by a tiered approach, using two high frequency stations visited by-weekly in combination with 9 stations sampled 6–9 times per year. Additional stations are included for mapping of winter nutrient and summer oxygen conditions. In the Eastern Gotland Basin, monitoring is currently restricted to coastal stations. The Latvian marine monitoring also includes assessment of contaminants.

The implementation of the Water Framework Directive was prepared in the framework of a cooperation project between the Danish Environmental Protection Agency and the Latvian Ministry of Environment. An international consultant company was contracted who prepared technical documents suggesting a typology of coastal and transitional waters as well as a system of reference conditions and class boundaries for high and good water quality classes. The national typology includes three water bodies in the Gulf of Riga – Gulf of Riga sandy coast, Gulf of Riga stony coast and Gulf of Riga transitional waters, as well as two water bodies at the Latvian coast of the Baltic Proper – Open Baltic stony coast and Open Baltic sandy coast. The division of water quality classes was based on literature information of the state of the ecosystem during the 1950ies and early 1960ies in combination with expert knowledge. Data availability did not allow defining quality classes for all parameters in each water body type. So far, quality criteria for high and good water quality classes were established for phytoplankton biomass and species composition in the Gulf of Riga transitional waters, phytobenthos depth limits on Gulf of Riga and Baltic Proper stony coasts, macrozoobenthos in the Gulf of Riga, as well as for transparency, oxygen and nutrient concentrations in all water types.

To adapt the Latvian marine monitoring program to the requirements of the WFD, more emphasis had to be put on marine monitoring in the coastal zone. Monitoring in the one nautical mile zone was intensified and additional stations were introduced. It is also planned to introduce systematic monitoring of phytobenthos, which so far has been surveyed only within pilot studies.

1.4.7 Lithuania

Lithuania signed (1992) and later ratified (1997) the Helsinki Convention on the Protection of the Marine Environment of the Baltic Sea Area. The requirements of the Convention and the Helsinki Commission were transposed into national legislation concerning the Lithuanian Baltic Sea environmental protection law, national liquidation plan of pollution incidents, regulations of soil dredging and soil management in the sea and harbor waters, control of foreign vessels, fishing in the Lithuanian economic zone and territorial waters, regulations of environmental monitoring and scientific-investigative works in the sea, etc. As Lithuania is one

of Contracting Parties therefore it has been engaged to follow and implement the HELCOM recommendations concerning the Baltic Sea monitoring program. Environmental monitoring of the Lithuanian territorial waters and economic zone in the Southeastern Baltic Sea has been carried out under the HELCOM COMBINE program, which addresses the monitoring of the open sea and coastal waters. The Southeastern Baltic Sea monitoring which contains hydrometeorological, hydrological, hydrochemical, ecotoxicological, hydrobiological, coast's dynamics investigations, has been carried out in 22 monitoring stations (coastal zone, open sea, recreational zone) every season. There are also 14 stations in the northern part of the Curonian Lagoon. The National Curonian Lagoon monitoring has been carried every month.

Beside the Center of Marine Research (CMR), as the main institution responsible for marine environmental monitoring, Lithuanian institutions, like the Fisheries Research Laboratory, Institute of Ecology, Institute of Geology and Geography, Klaipeda University, Geology Survey, etc. are also involved in marine monitoring and research.

Lithuania has been reporting on the implementation of HELCOM Recommendations (Rec.10/1 concerning abnormal situations in the marine environment, Rec. 12/1 concerning procedures for granting permits for monitoring and research activities in the territorial waters and exclusive economic zones, fishing zones or continental shelves, Rec. 12/9 concerning follow-up studies in connection with major oil spills, Rec. 13/1 concerning disposal of dredged spoils, Rec. 14/1 concerning monitoring of airborne pollution load, Rec. 18/1 concerning monitoring of radioactive substances, Rec. 19/3 concerning the Manual for the Marine Monitoring in the COMBINE Program of HELCOM, Rec. 19/4 Waterborne pollution load compilation 2000) under HELCOM MONAS.

In order to coordinate environmental monitoring and the scientific research in Lithuanian marine waters, store, analyze and spread the collected information, the Marine Environmental Data Fund has been established on the basis of the Center of Marine Research. All kinds of scientific-investigative researches and environmental / natural resources monitoring carried out by Lithuanian and foreign countries in Lithuanian marine environment are registered and data or reports are collected, and stored in the Data Fund.

Following EU recommendations, HELCOM and national requirements, a National Environmental Monitoring strategy for 2005–2010 has been prepared. In comparison with the previous Lithuanian Baltic Sea and Curonian Lagoon monitoring program, structural changes were introduced by determination of new water body categories – coastal and transitional waters within the WFD. The existing monitoring sites were classified into transitional (Curonian Lagoon and the plume from the Lagoon into the Baltic Sea) and coastal waters (one nautical mile for biological, and twelve for chemical monitoring). The monitoring of the open sea is

going to be carried out according to HELCOM and national requirements, which are applied to the transitional and coastal waters as well as the EU WFD. Identifying the coastal and transitional waters, as being 'at risk', operational monitoring is going to be carried out in these water bodies.

1.5 Summary

This report has outlined the fundamental principles of the monitoring requirements for the implementation of the EU Water Framework Directive. These principles have been related to the existing concepts within OSPAR and HELCOM. The main quality elements in the water framework have been described to set the frame for the selection of indicators in the covariation analysis (next chapter). The different national monitoring programs and national implementation of WFD was elaborated to assess if the WFD monitoring requirements are fulfilled.

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2. Covariation analyses

Uncertainty is inherent in the calculation of water quality indicators from monitoring data. The important question, however, remains how much of the variation is actually random and how much can be attributed to the specific circumstances of the sample. In monitoring programs observations underlie measurement uncertainty due to the processing of the sample, instrumentation error, addition of chemicals for the analysis, etc. and uncertainty due to patchiness, i.e. water masses and benthos are not homogeneous and samples may not represent as large an area as they are supposed to. Such sources of variation may be considered random as there are principally no means of describing how sample observations are affected by these. Hydrophysical and meteorological forcing of the marine ecosystem often influence the specific samples, e.g. by circulating and mixing water masses and resuspending sediments. These sources of variation may be considered systematic provided that relationships between observations of hydrophysical/meteorological forcing and water quality variables can be established.

In this chapter we will first give a description of the statistical principles used in the covariation analyses with a simulated example. An extensive list of potential variables to be employed in covariation analyses is given before the framework is exemplified with data from 7 sites from Nordic and Baltic countries.

2.1 Theoretical principles of covariation analysis

There are two important statistical components for estimation of a water quality indicator from monitoring data: bias and precision. Bias is a measure of whether an estimator is consistently too high or too low. The bias of an estimator $Z=h(Z_1, Z_2, \dots, Z_n)$ is defined as

$$\text{Bias}(Z)=E[Z-\theta]$$

where θ is the “true” value and $E[]$ denotes the expectation value. Thus, if Z is expected to give a true estimate of θ , bias equals zero and the estimator is said to be unbiased. The precision of an estimator relates to variability or consistency of that estimator. There is no formal definition for precision, but it is normally characterized by statistics such as variance, standard error or confidence interval. In statistical textbooks mathematical definitions have been suggested as both the inverse of the variance and the half-width of the 95% confidence interval. Overall, low variabil-

ity is associated with high precision and high variability is associated with low precision. In this report we will use the estimated standard error of the distribution as a measure of precision.

The objective of the covariation analysis is to obtain unbiased estimators for water quality with the highest possible precision by introducing explanatory variables (covariates) to describe the variation in our monitoring data. This means that the specific circumstances of individual samples, introducing bias and excess variation, should be accounted for through the formulation of functional relationships between observations and hydrophysical/meteorological observations. It is also important that a causal relationship between the response variable and the explanatory variables exists.

Assume that the marine ecosystem is controlled by two different governing factors (Fig. 2.1): External forcing (hydrophysical and meteorological variables) and anthropogenic pressure (typically nutrient inputs). Through the covariation analysis a clearer signal between anthropogenic pressure and indicators will be obtained, because variations caused by hydrophysical and meteorological fluctuations have been filtered out. If an indicator signals the combined process of external (X_i 's) and internal forcing (Y_i 's), both the hydrophysical/meteorological and internal variables should be included. Consequently, there are three types of covariate analysis:

Model A: No covariation with external forcing.

$$Z=h(Z_1,Z_2,\dots,Z_n)$$

Model B: Covariation with external forcing only

$$Z=h(Z_1,Z_2,\dots,Z_n)+f(X_1,X_2,\dots,X_n)$$

Model C: Covariation with external forcing and internal (within ecosystem) variables

$$Z=h(Z_1,Z_2,\dots,Z_n)+f(X_1,X_2,\dots,X_n)+g(Y_1,Y_2,\dots,Y_n)$$

In summary, the objective of the covariation analysis is to obtain precise and unbiased estimators of different indicators, where variations in external forcing have been taken into account. The covariation analysis includes the following steps:

- Select an indicator for the investigation (ex.: annual chlorophyll a concentration) and calculate the residual variation by means of the standard deviation.
- Screen potential external forcing variables (ex.: salinity, stratification, irradiance, temperature, mixing depth) and internal forcing variables (e.g. chlorophyll on secchi depths) that combined influence the individual observations.

- Make regressions (linear – non-linear relations) between observations used to compute the indicator and the external forcing variables.
- Investigate how this affects residual variance.



Fig. 2.1: Systematic sketch of internal processes and external factors acting on a coastal ecosystem. The objective of the covariation analysis is that the observed indicators should reflect a signal linked to pressures, cleansed for other, non-anthropogenic, sources of variation.

2.2 Normalisation of covariates

Let $Z_1, Z_2, \dots, Z_n$ describe the n observations sampled over a specific assessment period.

Model 0 (no adjustment at all):

Assuming that there are no covariates and no seasonality we can estimate the mean, standard error and confidence level for the mean over the assessment period by:

$$Z \in N(\mu, \sigma^2) \text{ or } Z = \mu + e_i$$

$$\hat{\mu} = \bar{Z} = \frac{1}{n} \sum_{i=1}^n Z_i$$

$$\hat{\sigma} = s = \sqrt{\frac{\sum_{i=1}^n (Z_i - \bar{Z})^2}{n-1}}$$

$$C.I. = \bar{Z} \pm t_{\alpha/2, n-1} \cdot \frac{s}{\sqrt{n}}$$

Model A (seasonal adjustment):

Assuming that the variable Z has a distinct seasonal pattern that can be described by monthly means or monthly deviations from the overall mean, m_j , $\sum m_j = 0$. The statistics then become:

$$Z \in N(\mu + m_j, \sigma^2) \text{ or } Z = \mu + m_j + e_i$$

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n Z_i - m_j$$

$$\hat{\sigma} = s = \sqrt{\frac{\sum_{i=1}^n (Z_i - \hat{\mu} - m_j)^2}{n-1}}$$

$$C.I. = \hat{\mu} \pm t_{\alpha/2, n-1} \cdot \frac{s}{\sqrt{n}}$$

It should be noted that the nominator for estimating the standard error is equal to the sum of the squares residuals. In case m_j values have been estimated by means of $Z_1 \dots Z_n$, the degrees of freedom for estimating the standard error and confidence interval are not entirely correct. However, the error is marginal if the monthly means have been calculated over many assessment periods and there are relatively many observations in the assessment period.

Model B (seasonal adjustment and covariation with external forcing):

Assuming that the variable Z has a distinct seasonal pattern (same assumptions about m_j as in Model A) and covariates with an external forcing variable X that we can associate with a standard value of X_s (e.g. the long-term mean) and a is a regression coefficient for the relationship. The statistics are then:

$$Z \in N(\mu + m_j + a \cdot (X - X_s), \sigma^2) \text{ or } Z = \mu + m_j + a \cdot (X - X_s) + e_i$$

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n Z_i - m_j - a \cdot (X_i - X_s)$$

$$\hat{\sigma} = s = \sqrt{\frac{\sum_{i=1}^n e_i^2}{n-1}}$$

$$C.I. = \hat{\mu} \pm t_{\alpha/2, n-1} \cdot \frac{s}{\sqrt{n}}$$

Model C (seasonal adjustment, covariation with external forcing and internal variable):

Assuming that the variable Z has a distinct seasonal pattern (same assumptions about mj as in Model A) and covariates with an external forcing variable X that we can associate with a standard value of Xs (e.g. the long-term mean) as well as an internal variable Y (using a regression coefficient b) that also signals the anthropogenic pressure. The statistics are then:

$$Z \in N(\mu + mj + a \cdot (X - Xs) + b \cdot (Y - \bar{Y}), \sigma^2)$$

or $Z = \mu + mj + a \cdot (X - Xs) + b \cdot (Y - \bar{Y}) + e_i$

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n Z_i - mj - a \cdot (X_i - Xs)$$

$$\hat{\sigma} = s = \sqrt{\frac{\sum_{i=1}^n e_i^2}{n-1}}$$

$$C.I. = \hat{\mu} \pm t_{\alpha/2, n-1} \cdot \frac{s}{\sqrt{n}}$$

Note that the values of Y_i are not used in calculating the mean level, since $\hat{\mu}$ should only be adjusted for variations in the external forcing. This also follows from the formulation of the model since.

$$\sum Y - \bar{Y} = 0$$

Thus, the effect of including an internal variable as covariate is to reduce the variability of the indicator, i.e. increasing the precision of the indicator. This implies that if we calculate indicators for different assessment periods these are compared based on similar levels of the external forcing but to different levels of the internal variable which also is affected by the anthropogenic pressure. Moreover, if the model parameters are estimated from data then a more precise and less biased (hopefully unbiased) estimate of a will be obtained by including Y into the regression.

Caution should be exercised when including internal variables to explain variations in the observations, since the model should be based on causal relationships. For example, chlorophyll a is an internal variable that can be used to explain variations in secchi depths, but secchi depths can not be used to explain variations in chlorophyll although the correlation probably exists.

It should also be stressed that the calculations above do not take the uncertainty of the parameter estimates of a and b into account, they have been assumed well determined. This will only have marginal effect if the average of the external forcing is close to the long-term mean ($\bar{X} \approx Xs$),

but if the external forcing conditions for one year deviate strongly from the long-term average the uncertainty of a should also be considered when calculating the confidence interval.

2.2.1 Example of normalization

Let Z be Secchi depths, X be wind speed and Y be chlorophyll. Secchi depths depend on the scattering of light, and chlorophyll and suspended sediments are two major components for attenuating light in the water column in coastal areas. Thus, chlorophyll is an internal variable that may explain variations in Secchi depths. In shallow waters the resuspension of sediments during high wind conditions suggests that wind speed could be an external forcing factor for Secchi depths. It is therefore included as external variable.

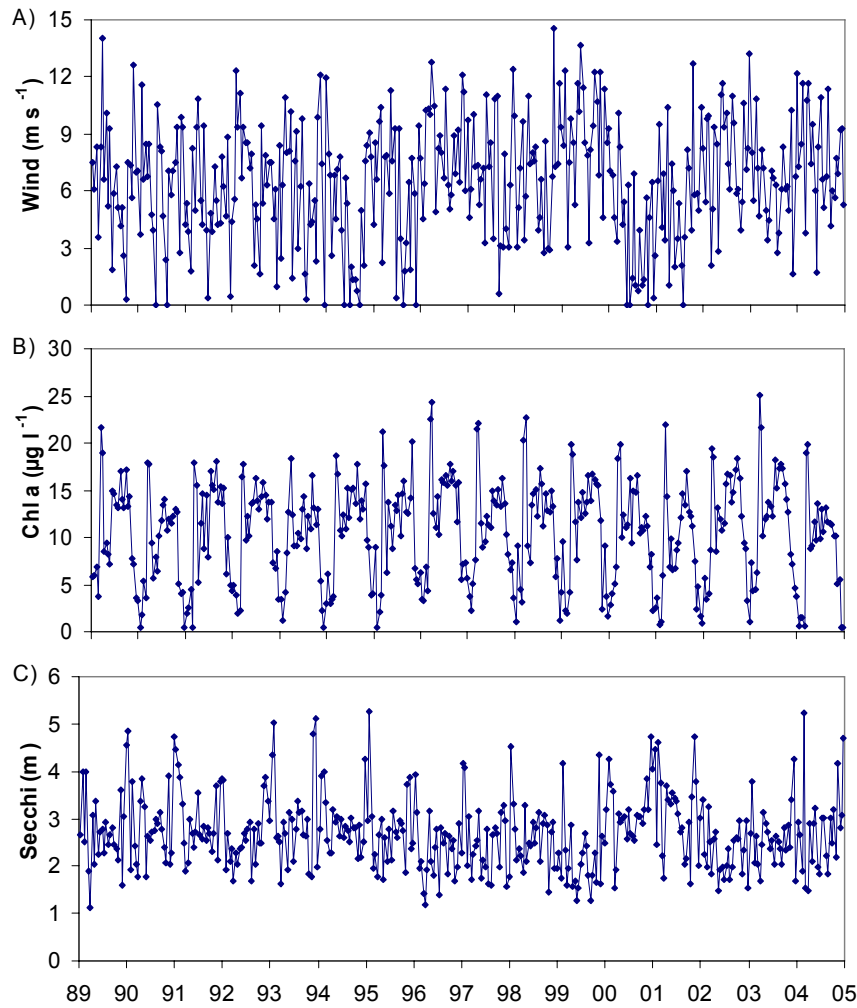


Fig 2.2: Simulated time series for A) wind speed, B) chlorophyll and C) secchi depths.

These three variables were simulated using simple relationships to link Secchi depths to the two other variables, including a seasonal component and noise on all variables (Fig. 2.2). Calculating the annual Secchi depth by means of the methods described above yields no difference between mean values obtained from *Model 0* and *Model A* (Fig. 2.3), because the data set is balanced by having the same number of observations per month for each year. There would be a difference if some of the observations were missing as *Model A* weights the observations by the months taken. For all years combined the estimated standard error of the residuals was reduced from 0.75 m (*Model 0*) to 0.65 m (*Model A*).

The indicator changed mean levels when calculated by means of *Model B* and *C* (giving similar results) and the estimated standard error of the residuals was further reduced to 0.40 m (*Model B*) and 0.36 m (*Model C*). The indicator levels differed by up to 11% from the models without covariates (*Model 0* and *Model A*) to the models with covariates (*Model B* and *C*).

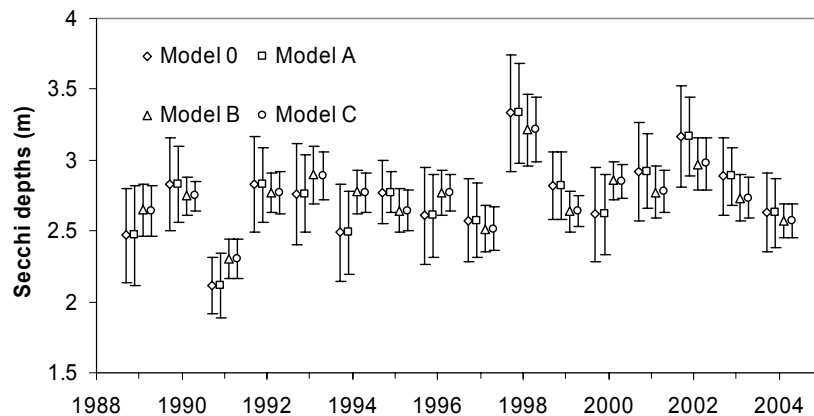


Fig 2.3: Annual mean of secchi depth calculated by the 4 proposed models. Error bars show the 95% confidence of the mean.

2.3 Indicator variables and external forcing covariates

In this study indicator variables are seen as high-level complex monitoring variables, which contain information on central biological processes or states (e.g. organism abundance, species richness, pigment concentration, Secchi depth, total nitrogen or total phosphorous). Such indicator variables may be used to assess changes in the environmental state of an ecological system, where the cause of change is often anthropogenic influence. The approach of the Water Framework Directive (WFD) is to use indicator variables to classify the ecological status of aquatic systems, in relation to reference values, to maintain or achieve a good ecological status. This project has focused on removing variability in indicator vari-

ables induced by short-term fluctuation in external forcing. In general human activities or internal biological processes do not affect the external forcing. Typical external forcing variables are temperature, salinity, wind speed, wind direction, wave action, currents, insolation, precipitation etc. These are here considered as covariates and may induce variation on different spatio-temporal scales. It is desirable to remove the residual variation in monitoring variables caused by short-term fluctuations of these covariates. The goal is to increase the precision of between year estimates of indicator variables by normalizing them to a “standard year” which is in covariance analysis generally the average year (i.e. the average of the covariate or covariates).

Internal variables are estimates relating to biogeochemical processes in the system, which may result in changes in the indicator variables (e.g. nutrient uptake, primary production, grazing, sedimentation, competition, toxic effects etc.). The effects of these variables must be normalized with great caution since the direction of causal relation between them and the indicator variables is often unclear. For example does production as such not affect total nitrogen concentration in the upper mixed layer since it is only a transfer of nitrogen from inorganic to organic form. The resulting sedimentation however results in a net decrease of total nitrogen concentration in the upper mixed layer. High total nitrogen concentration may also be a prerequisite for high production if there is a large component of inorganic nitrogen. Another example is the relation between chlorophyll *a* and Secchi depth discussed in Section 2.2.1. Because of the complicated causality of these internal variables it is possible that they partly or wholly measure another aspect of the indicator variables. Using them as covariates to normalize to a standard value may remove relevant effects in the indicator variables. There are also many other less complex variables that may be used to analyze the ecological status of a given system (e.g. inorganic nutrients, tissue concentrations of specific toxic contaminants, oxygen level etc.). These may be as relevant as the high-level indicator variables but are often contained in them (e.g. are nitrate and ammonium parts of total nitrogen) or has a direct impact on them (e.g. toxin levels and abundance). They are therefore often strongly correlated with the high-level indicator variables or the direct cause of changes in the latter. This internal relation between high level indicators and their components or the system internal dynamics was not studied in this project.

The external forcing variables act on many temporal scales and it is not evident which scale should be used to normalize. The most intuitive normalization is to a standard year but in many cases this may not be the appropriate scale since many external forcing variables vary in cyclic patterns over several years (e.g. temperature, precipitation, NAO). They may also themselves undergo a change on the climate time scale (e.g. global warming). Normalizing to a standard year would then remove actual effects in the indicator variables. It is therefore important that

changes in the covariates only affect the residual variation in the indicator variables. Sometimes this is difficult to assess since the covariates are also measured with uncertainties. In most cases they are however measured with considerably higher precision than the indicator variables. In the following section some important external forcing variables are discussed as covariates to indicator variables.

2.4 Potential mechanisms for covariation

Since covariance analysis is a regression approach it is central that there is a plausible causal relation between the covariate and the indicator variable. In many cases this is relatively straightforward but since the external forcing variables affect most biogeochemical processes the causal relation may sometimes be unclear which reduces the credibility of normalization. For some covariates there are general causal mechanisms, which can be expected to propagate variation in the covariate to the indicator variables. The covariates themselves are however also likely to be partly interdependent (e.g. wind speed – wave height, insolation-temperature). In the following some important covariates and their potential impacts on indicator variables will be briefly discussed.

2.4.1 *Water temperature*

Seasonal changes in water temperature have profound effects on most biological processes in the waters of the temperate region. Corrections for seasonality are therefore to a large extent a temperature correction. There are several mechanisms, which relate within season variation in temperature with indicator variables. Increasing temperature, leading to water column stratification, and insolation triggers the spring bloom. Estimates of spring bloom primary production are therefore likely to be sensitive to variation in these two covariates. Increasing insolation causes increasing water temperature and stratification, but the temperature is also affected by air temperature and water circulation. The spring bloom generally has a very pronounced peak and the timing of sampling is therefore essential. If primary production is estimated at specific dates with low frequency there is a considerable risk that interannual differences in the development of water temperature and stratification will cause large differences in estimates of primary production. Correcting these values for the covariates temperature and insolation is in this case not likely to improve the annual averages of primary production, biomass, chlorophyll *a*, Secchi depth or sedimentation during the spring bloom since the effect may only be a time lag. If the spring bloom is sampled during its entire duration it is much more likely that covariate analysis will increase precision of averaged or integrated estimates of indicator variables. The correction

will then remove actual interannual differences caused by differences in the averages of the covariates for the entire duration of the spring bloom. If the indicator variable is species-specific abundance or a diversity index the water temperature may also affect the species composition of phytoplankton by their temperature preferences with higher abundances of cold water species in cold year and vice versa.

During *summer* it is difficult to discuss effects of water temperature in general terms. The spring bloom is a temperature/stratification and insolation driven transfer of inorganic nutrients to biological material and a considerable part sediments out of the water column. During the stratified summer period rapid internal mineralization-assimilation processes characterize the pelagic system. Generally biological process rates increase with increasing temperature, but since most indicator variables are amounts rather than rates, the effects of normalizing moderate temperature differences may be small during summer. In shallow areas there are however several mechanisms by which elevated water temperature may affect indicator variables. Decomposition of organic material in sediments and algal mats increases with increasing temperatures and may cause oxygen deficiency and increased release of nutrients in areas with limited water circulation. This may locally affect the primary production and the composition of benthic fauna. Many fish species also actively avoid very warm water and may migrate to greater depth at extreme temperatures. High water temperatures will favour microbial decomposers and benthic species with high oxygen demand may die or migrate out of the area. In the Baltic Sea the pelagic filamentous cyanobacteria are dependent on high water temperatures and may in warm summers with high phosphate concentration in the surface water form very extensive blooms. The blooms directly affect chlorophyll *a* levels but also, through nitrogen fixation, the concentration of total nitrogen above the pycnocline. If water temperature and insolation remain high during *autumn*, blooms of mainly diatoms may occur when the nutrient supply increases by sediment mineralization and reduced stratification strength.

In coastal waters in the Baltic Sea the salinity depth gradient is often not strong enough to identify horizontal and vertical transport of water masses. During summer the temperature is in many cases a more sensitive variable to identify exchange of water masses. Particularly upwelling of deep water can affect variables as chlorophyll *a* and nutrient concentrations drastically and cause anomalies in data, which increase residual variation. These situations can often be identified as drastic drops in surface temperature in combination with strong winds. Since the events are episodic it is unlikely that such anomalies can be corrected by normalization according to a continuous causal model. It is in those cases preferable to remove the data from the set if the rate of change in water temperature exceeds what can physically be explained by insolation and heat exchange between air and water.

2.4.2 *Insolation*

It is in most cases difficult to separate direct effects of insolation from those of water temperature in monitoring data, since they are likely to be cross-correlated in time frames which are generally relevant in monitoring. Insolation is variable on shorter timescale than water temperature and production data must always be viewed in this perspective. During periods of very high production and sedimentation (e.g. spring bloom) insolation may potentially also be reflected in the chlorophyll *a*. During late autumn blooms with increasing nutrient levels insolation is also likely to be the limiting factor and may therefore be useful for normalisation of primary production and chlorophyll *a*. Very large variations in light intensity as such may also potentially affect estimates of Secchi depth.

2.4.3 *Salinity*

Salinity strongly affects most indicator variables in the Baltic region. It has been evaluated as covariate in all examples of normalization in this project (Sect. 3), and normalization to average salinity has in many cases been shown to considerably reduce residual variation in indicator variables. In situations where the monitored indicator variable is affected by mixing of two waters with different salinity, normalization with a linear model is highly likely to be useful to remove residual variation. The causality in this situation is generally not that short-term variation in salinity affects the biological processes as such, but rather a direct result of mixing of waters with different character. In most monitoring situations the freshwater source is most affected by anthropogenic activity (e.g. elevated nutrient levels), but there are also oligotrophic rivers in the northern parts of the Baltic Sea. The situation where a eutrophicated freshwater is mixed with marine water is an almost ideal situation to increase precision by a salinity covariance normalisation. This is clearly seen in the Limfjorden estuary (Sect. 3.7) where the water exchange with North Sea and the Kattegat forces the total nitrogen and phosphorous concentration in the estuary.

Salinity can also be expected to affect indicator variables in archipelagos and open coastal areas but the interpretation is here considerably more complex. Wind induced horizontal and vertical water transport may result in rapid changes of indicator variables. Strong upwelling transports nutrient rich deep water into coastal areas, which during summer stratification results in increased availability of inorganic nutrients and removal of surface water with high abundances of plankton organisms and nutrients in organic form. This can cause changes in species composition where plankton with lower temperature optima and high assimilation efficiency are favoured. Such episodic exchanges of water packages are not likely to be successfully adjusted by covariance analysis (see Temperature). To treat data from such occasions as anomalies and removing

these data from the set is more likely to reduce residual variation in a meaningful way. There are, however, complications with this approach as well. If the plankton community changes, the effects of the water exchange may last for some time after the event. The question then arises of how long after the event the estimates of indicator variables should be seen as anomalies. An example of this is the summer cyanobacterial blooms in the Baltic proper. The filamentous cyanobacterium *Nodularia spumigena* can by onshore wind accumulate to very high abundances in coastal areas resulting in locally high concentrations of organic matter and chlorophyll in surface water. When these accumulations are removed from coastal areas by upwelling it can locally cause drastic changes in abundance estimates, species composition and most indicator variables. It is here not clear if this is to be seen as an anomaly or if these large variations are to be seen as a part of natural residual variation.

Many quality criteria in the WFD are based on estimates of diversity and abundance. High diversity and abundances in combination is in most cases an indication of high ecological status. The Baltic region represents a diversity minimum between limnic and marine conditions with a combination of marine and limnic organisms under salinity stress and true brackish water species. Variation in salinity over time is therefore likely to cause changes in species composition. Most species are obviously tolerant to moderate changes in salinity and correction by covariance analysis is therefore not likely to be successful in reducing short term residual variation. Normalization over longer time periods is also questionable since it may remove an actual salinity dependent trend in the indicator variable rather than residual variation.

2.4.4 Precipitation and freshwater runoff

In unregulated water systems runoff is a time-lagged reflection of precipitation or snow melting. To avoid time lags the effects of this covariate are in most cases likely to be better normalised through changes in salinity in the studied water body. Direct precipitation on the open water surface of marine systems is generally not a factor that substantially affects indicator variables in the Baltic region. These effects on salinity are ephemeral and limited to the water very close to the surface. High nitrate levels in rain main potentially, in periods of very intensive rain during summer, cause elevated levels near the water surface but the amounts are generally small in relation to those in circulation in the upper mixed layer.

2.4.5 Ice coverage and timing of ice break-up.

In areas irregularly covered by ice, cold winters with ice cover may cause the spring bloom to be later, more intensive and shorter in duration than in years without ice cover. The most likely reason is that the production is

delayed by light limitation imposed by the ice cover and that the light intensity therefore is higher when the spring bloom eventually starts. This may cause very high chlorophyll *a* levels in the early stage of the spring bloom, which may if they are singular observations be misinterpreted. To normalize this effect is very difficult since there is no good continuous estimator of ice cover. The water temperature is not useful since the break up of the ice occurs in connection with storms, and therefore is likely to cause large transport of water. To use the average chlorophyll *a* or integrated production for the entire spring bloom with a high sampling frequency is the only reliable method to avoid this problem.

2.4.6 Wind

Variable wind speed, direction and duration are likely to cause short-term variation at many open coastal and estuarine stations, particularly in areas with limited water depth. There are three major causes for effects: (1) Wind driven horizontal or vertical exchange of water (e.g. upwelling). (2) Wave induced resuspension of sediment material and fragmentation of algal material. (3) Increased mixing and associated deepening of the thermocline.

Wind driven water exchange occurs at all stations and is highly dependent on the bathymetric conditions at the station. Upwelling of deep water has been discussed under the headings Temperature and Salinity. Wind events may however cause water movements on many spatio-temporal scales. Langmuir circulation may aggregate particles in open water within hours in long thin stripes, a few meters wide and a nautical mile or less long, whereas Ekman transport can move water on the scale of weeks and hundreds of nautical miles. All such water movements are likely to be reflected as short-term variation in indicator variables.

Wind induced resuspension of epibenthic algae and sediment, and fragmentation of particularly filamentous algae, is likely to cause considerable effects on many indicator variables in shallow areas. The increased amount of particles in the water column directly affects estimates of Secchi depth, chlorophyll *a*, sedimentation and total nitrogen and phosphorous concentrations. In the upper mixed layer the direct effects are likely to be short in duration since most particles are removed by sedimentation within days. Concentration of inorganic nutrients and other substances may however also be indirectly affected by release from the particles.

Normalization of wind speed effects is complicated by the direction, fetch and duration of the wind event. In open coastal sites it may be possible to identify groups of wind directions with different effects and to normalize by wind speed and duration within these groups. In archipelago areas this is however likely to be very complex. In such areas the estimates of wind induced water transport patterns is generally not sufficient to be used as a covariate, since the covariate should be measured with at

least the same precision, and preferably higher precision, than the indicator variable. The increase of particles in the water of shallow areas is however likely to be easier to address. The wind directions, causing wave action on the sediments are generally easy to identify and the effect can than be assumed to depend on wind speed and duration. A more direct measurement would be wave height but this is seldom measured at the specific site and can vary considerably within small distances.

2.4.7 Wave action and current speed

Wave height and duration (perhaps recalculated to total wave induced energy on the littoral zone during an event) are likely to be highly useful covariates for correction in shallow areas (see Wind). The effects are often dramatic and affect most indicator variables by increasing the amounts of particles in the water. Continuous registration of wave height may therefore be a useful tool to reduce residual variation in annual averages of indicator variables from such areas. In many situations the currents may cause transport of particulate material and plankton. Transport of material in benthic flows, along the sediment surface, may at high current speeds cause elevated levels of organic material in water samples taken near the sediment. The current speed as such is also a momentary indication of the intensity of water exchange with other water bodies. At stations located in sounds or in other areas, where strong currents often appear, the speed of the current is likely to be reflected in estimates of particulate matter and total nutrients. If any measurement of sedimentation rate is estimated at such stations it is likely to be strongly dependent on current speed. The most pronounced situation where current speed may affect indicator variables is in estuaries with narrow inlets and significant tidal amplitude.

2.4.8 Some other potential covariates, which may be useful for normalization.

There is of course a multitude of other potential covariates, which may be more or less site-specific, and just a few can be mentioned. *Stratification strength and depth* may affect the exchange of water and nutrients between the winter water and the photic zone. The *North Atlantic Oscillation* (NAO) has been shown to impose cyclic patterns in many ecological variables in marine systems of the northern Atlantic region. *Known emission events from specific from specific point sources* may be useful to remove episodic variation in indicator variables from stations located near the source.

2.5 Examples of covariate normalization

In the following examples from different areas some important indicator variables have been normalized by external forcing covariates. In some cases normalization by internal covariates has also been evaluated and discussed. The areas represent a wide variety of coastal marine and brackish water environments. Laajalahti and Vanhankaupunginlahti bays, Coronian lagoon and Limfjord represent estuarine systems whereas the Moonsund, Gulf of Riga and Askö are more representative of open coastal sites. The Oslofjord is an example of a true fjord with water exchange limited by sills and is together with the Limfjord the most marine environments in the study. The lowest salinities in the study are found in the Laajalahti and Vanhankaupunginlahti bays and the Coronian lagoon.

2.5.1 *Oslo fjord example*

Introduction

The Oslofjord is located in the Southeast part of Norway, with the capital Oslo at the northern, inner end (Fig. 2.4). The fjord is surrounded by the most densely populated region in the country, and the fjord is intensively used for recreational purposes. The inner part of the fjord has a surface area of about 190 km², with two main basins, Bunnefjord and Vestfjord. The two main basins have maximum depths of about 160 m. The deeper parts of the basins are closed off from each other by a sill at 54 m depth, and the outer basin is closed off from the outer fjord by a narrow sound with a sill at 20 m deep at Drøbak. In the western basin, the deep water masses are renewed by major inflows over the sill every winter, while in the eastern basin they may be stagnant 3 to 4 years between each major renewal.

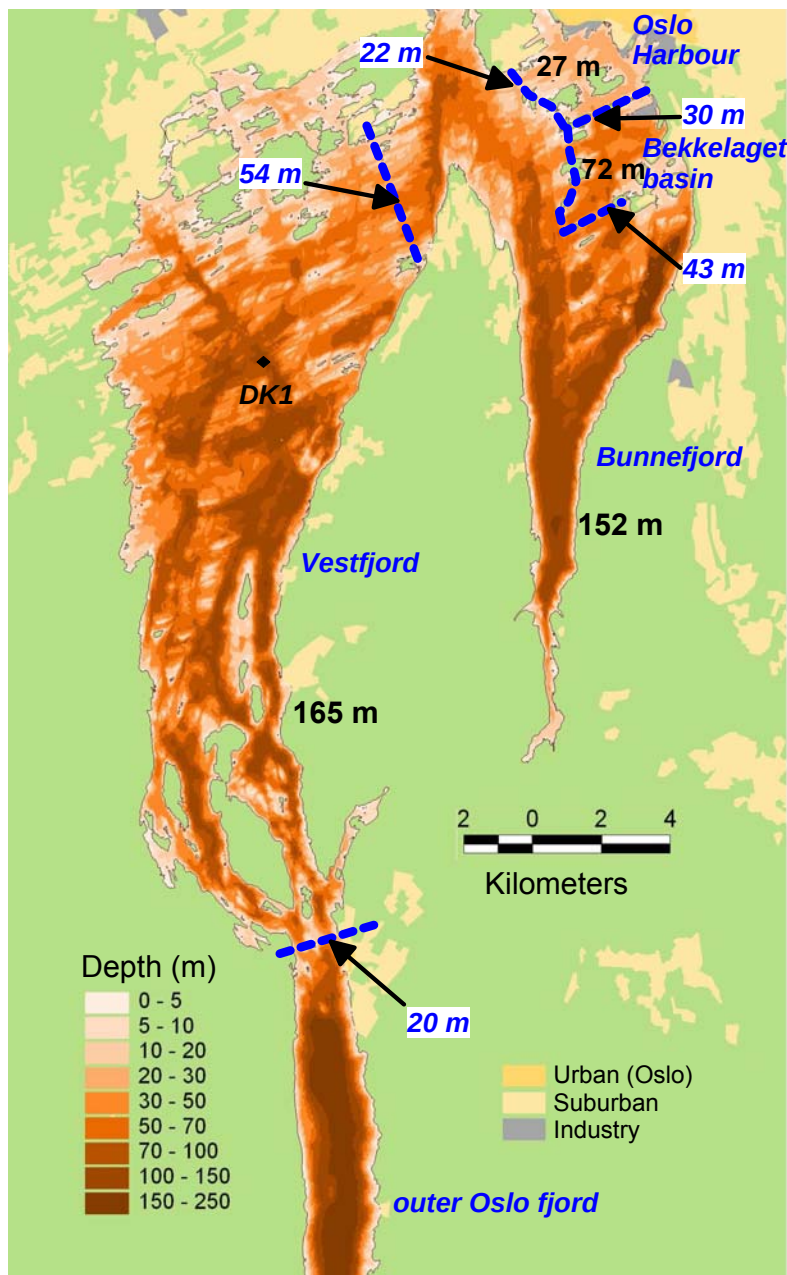


Fig. 2.4: Topographical map of the inner Oslofjord, Norway.

Direct freshwater input to the inner fjord is only about $20\text{--}30 \text{ m}^3 \text{ s}^{-1}$. In spite of this there is a marked vertical stratification throughout most of the year, with surface salinities from 25 to 15‰. This is because the larger outer fjord receives more than $1000 \text{ m}^3 \text{ s}^{-1}$ of freshwater from two large rivers, and this strongly influences the vertical stratification in the inner fjord. The tidal amplitude is 20–30 cm, with wind and pressure-induced variations normally within 1 m from mean level, so the water exchange is limited even for the surface layers.

The fjord receives sewage from about 800,000 inhabitants in the Oslo region. The nutrient inputs peaked around 1970 and have since been reduced by 90% in phosphorus and by 60% in nitrogen (Fig. 2.5). Consequently, the water quality of the surface layers has clearly improved compared to the 1970's.

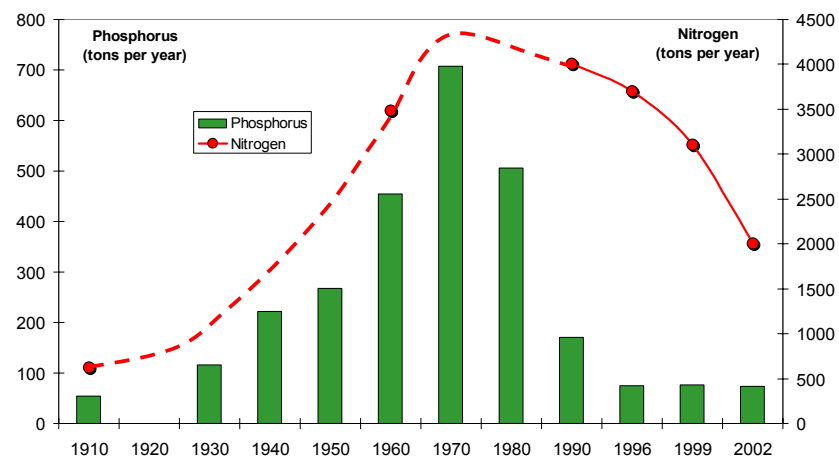


Fig. 2.5: Development of total runoff of nitrogen and phosphorus to the inner Oslo fjord from 1910 to today (Magnusson et al. 2004).

Materials and Methods

The fjord has been continuously monitored since 1973, on average with 6 cruises per year, most often in February, April, May, August, October and December, but with some variation between years both in frequency and selection of variables. Data has been collected from depth profiles at a number of fixed stations. The present study focuses on a subset of these data, from the surface layer at station DK1 in the largest basin, shown in Fig. 2.4.

The surface layer has normally been sampled at 0 and 4 m depth, but sometimes only values from 4 m are present in the data, and the surface sample is sometimes recorded as being taken from 0.5 or 1 m depth. Inspection of the data show that in general there is little difference between simultaneous data from 0 and 4 m depth compared to variations between succeeding observation dates, so to have as complete a data sets as possible, the data have been aggregated into averages over the 0–4 m depth interval before further analysis. Results are presented in annual monitoring reports (Magnusson et al. 2003, 2004).

Response variables

The present study focuses on total nitrogen and total phosphorus as eutrophication indicators, using data for all seasons of the year. The time series for total nitrogen has a gap for years 1985 to 1990, when nitrogen was not included in the monitoring program. For total phosphorus the data series cover all years from 1973 to 2004. Winter values of phosphate

and nitrate have also been considered for analysis as eutrophication variables, but for the inner Oslofjord there is a very strong linear relationship between phosphate and total phosphorus in winter, so studying winter phosphate in this data set will hardly contribute more to the covariate study than looking specifically at winter values of total phosphorus. The same is true of the relation between nitrate and total nitrogen, at least for the period after 1991, which is most relevant for the present issue of classifying water bodies. Thus total phosphorus and total nitrogen have been analyzed as the main eutrophication response variables. In addition, the study looks at chlorophyll data for months June to August.

Covariates

Salinity and temperature are explored as the primary covariates or parameters for natural variations in stratification, freshwater influence and horizontal movements that may influence the eutrophication indicators. In addition, meteorological observations from the Norwegian Institute for Meteorology taken each 6 hours at Blindern, Oslo have been explored as covariates. The meteorological variables selected for the study are temperature, cloud cover as parameter for solar radiation (daylight observations at hours 7, 13 and 19), wind components North, South, East, West, and in addition total Wind speed to 3. power to represent mixing energy. Wind components from North or South were put in separate variables to allow for independent assessment of possible effects, the same was done with wind components from East or West. For the meteorological variables, used the average on the observation date and the average over the two previous days were explored as covariates.

Statistical analysis

The purpose of the covariate analysis is to find ways to correct data for the 'noise' in the data, that is, the variations caused by other factors than changing anthropogenic impact, so that the 'signal', which is the effect of this impact, can be estimated as precisely as possible. The eutrophication response variables have a pronounced seasonal cyclic pattern of a deterministic character, caused by a combination of physical and biological factors in a complex cause-effect network. There are also long-term trends in the eutrophication indicators due to changing anthropogenic impact (increased pressure, abatement measures), but these trends should be part of the signal to be analysed when classifying a water body or assessing time trends and should not be removed by corrections for covariates. It is mainly the short-term, within-season variations around the main seasonal and long-term trends that should be sought to be reduced by relating them to similar variations in physical covariates.

For total nitrogen and phosphorus, where data from the whole year are analysed, it has been chosen first to remove the regular seasonal variation both for response variables and covariates temperature and sa-

linity, which all have a pronounced seasonal variation. Because the distribution of observation over months varies over years, and not all months are equally well covered by observations, the seasonal modeling is done by adapting a continuous seasonal cyclic model instead of using a fixed month factor. The model has up to three Fourier terms to the time series (Y_i, t_i) , $i=1, \dots, n$:

$$Y_i = \mu + \sum_{k=1}^m A_k \cdot \sin(2k\pi(s_i + \theta)) + Y_i^*$$

($m \leq 3$; s_i = time within year $[0 \dots 1]$ of obs. i)

The residuals Y_i^* retain between-year changes and the short-term, within-season variations in the data. For the eutrophication response variables, the long-term trends are extracted from these series by fitting a smooth, non-linear trend in time series plots of the residuals, Y_i^* , using negative exponential smoothing. The smoothed values (S_i, t_i) are subtracted to give detrended residuals $Y_i' = Y_i^* - S_i$ that describe only the short-term within-season variation. This is done for the eutrophication indicators only; covariates salinity and temperature have much less long-term variation, and between-year variations on a 25–30 year time frame should be seen mainly as a result of natural fluctuations that might affect indicator variables, so it is natural to keep them in the covariate signal for possible correction of the indicator variables.

For the meteorological covariates, the seasonal variations are much less important, and they are used directly, without using long-term and seasonal trends. All statistical analyses were done with Statistica v.7.1 (StatSoft, Inc. (2005), www.statsoft.com).

Results

Conditions in the surface layer in the inner Oslofjord have pronounced seasonal patterns. Fig. 2.6 shows the seasonal variation of surface temperature and salinity. Temperature follows a near sinusoidal curve, with small within-season variation from year to year. Salinity also has a clear seasonal pattern, but with larger within-seasonal variation. In winter stratification is weak, with surface salinities from 26 to 32. The salinity at 50 m depth varies between 32 and 34, with only weak seasonal variation. In spring, a stronger stratification develops, and summer salinities in the surface layer range from 15 to 25. The summer pycnocline is typically found at about 10 meter depth.

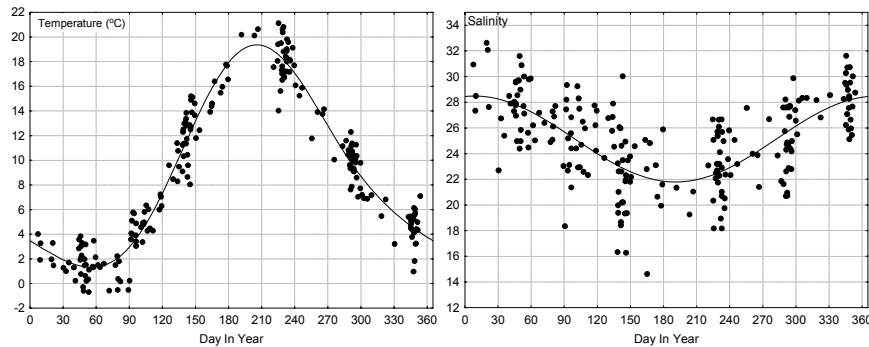


Fig. 2.6: Seasonal variation of temperature and salinity at station DK1, 0–4 m average, with adapted seasonal models.

Phosphorus and nitrogen concentrations vary in response to human impact, mainly on the long term, and in addition have regular seasonal variations and irregular short term and medium-term variations between years. The seasonal patterns of phosphorus and nitrogen are results of both physical and biological factors. River runoff is normally low in winter and variable through the rest of the year, with peaks due to snow melting in spring and rainfall, particularly in the autumn but with different patterns from year to year.

Increased stratification in summer caused by surface heating and larger freshwater runoff leads to lower vertical mixing between surface waters and nutrient-rich deeper waters. This combines with the effect of primary production which transports biologically bound nitrogen and phosphorus away from the surface layers by sinking organic matter in giving lower surface concentrations of total nitrogen and phosphorus. Meteorological variations influence these processes in various ways.

The seasonal and the long-term variation of total nitrogen are shown in Fig. 2.7. The seasonal plot shows a clear pattern, with high values from 300 to 700 $\mu\text{g N l}^{-1}$ in winter, and about half of that in summer. The time series plot indicate a decrease from 1995, and the concentrations are particularly low for the last couple of years, possibly a beginning effect of nitrogen removal introduced from 1995 to 2000. The plots of total phosphorus in Fig. 2.7 show a similar picture, with a seasonal variation between high values (25 to 70 $\mu\text{g P l}^{-1}$) in winter and low values (3–10 $\mu\text{g P l}^{-1}$) in summer, and the time series plot gives a visual impression of a long-term decrease in both high winter values and low summer values.

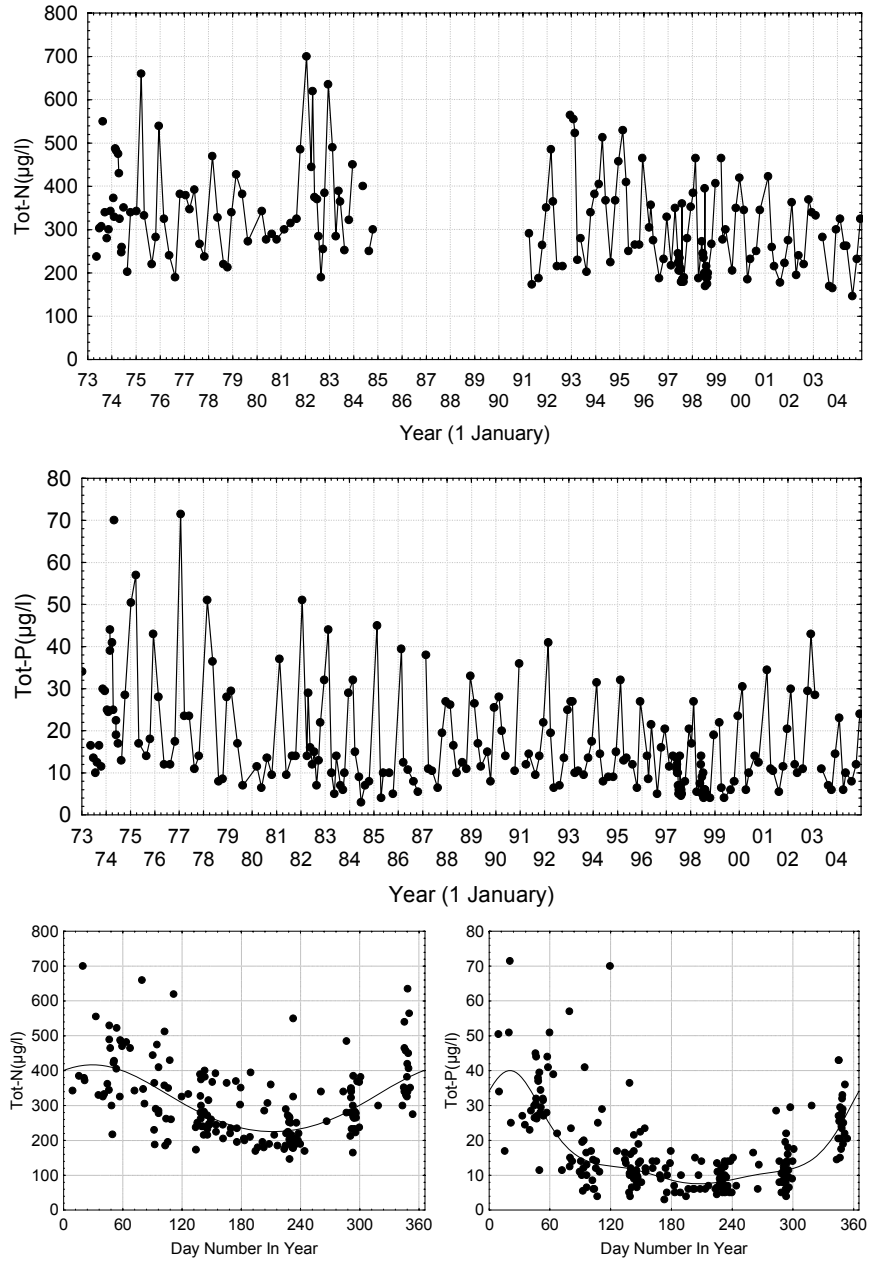


Fig. 2.7: Total nitrogen and total phosphorus at station DK1, 0–4 m average, against season and as time series

The seasonal plots also include the Fourier model curve fits, with parameters as shown in Table 2.1. Only the terms where A_i is significant has been kept in each model. For total nitrogen and phosphorus, the model is adapted to the logarithms of the concentrations, since this fits the variation pattern and residual distributions better, and avoids the problem of negative fit values.

Table 2.1: Parameters in seasonal models adapted by least squares method

dependent variable (Y)	μ	A_1	θ_1	A_2	θ_2	A_3	θ_3
Temp [°C]	9.244	-8.6677	1.0153	-1.7086	4.3382	not significant	
Salinity	25.142	3.3507	1.4266		not significant		
ln(totN [$\mu\text{g N l}^{-1}$])	5.725	0.3078	-61.879		not significant		
ln(totP [$\mu\text{g P l}^{-1}$])	2.681	0.692	-66.067	0.179	-29.162	0.142	-10.103

The residuals from the seasonal models for natural logarithms of total N and total P are shown in Fig. 2.8, with nonlinear long-term trends fitted. Residuals are de-trended by subtracting the trend fit, resulting in a time series of deviations on the log scale without seasonal or long-term changes. Table 2.2 summarises the reduction in variance of logtransforms of concentrations as a result of the correction for seasonal and long-term variation.

Table 2.2: Reduction of variance of natural logarithms of concentrations by removing seasonal and long-term trend

Variance term on natural log scale	TN	TP
Observations	0.111	0.429
Deviations from average seasonal pattern	0.0651	0.1996
Residual deviation after removal of both seasonal pattern and long-term trend	0.0514	0.1493

Time series plots show, however, that medium-term variations on a 5–10 year scale remain in the residuals, they could possibly be related to similar medium-term variations in the covariates (Fig. 2.8). The detrended residual are transformed back into the linear concentration scale, giving residual *factors* (F_{residual}) that describe the relative variation around the expectation value given by the seasonal pattern and the long-term trend. This can be described as a multiplicative model:

$$\text{Concentration} = A_{\text{Season}} \cdot B_{\text{trend}} \cdot F_{\text{residual}}$$

The residual factors are finally correlated to natural covariates, assuming that they may be the result of events that affect both the nutrients and the covariates. The right panes in Fig. 2.8 show the residual factors against salinity as deviation from seasonal pattern.

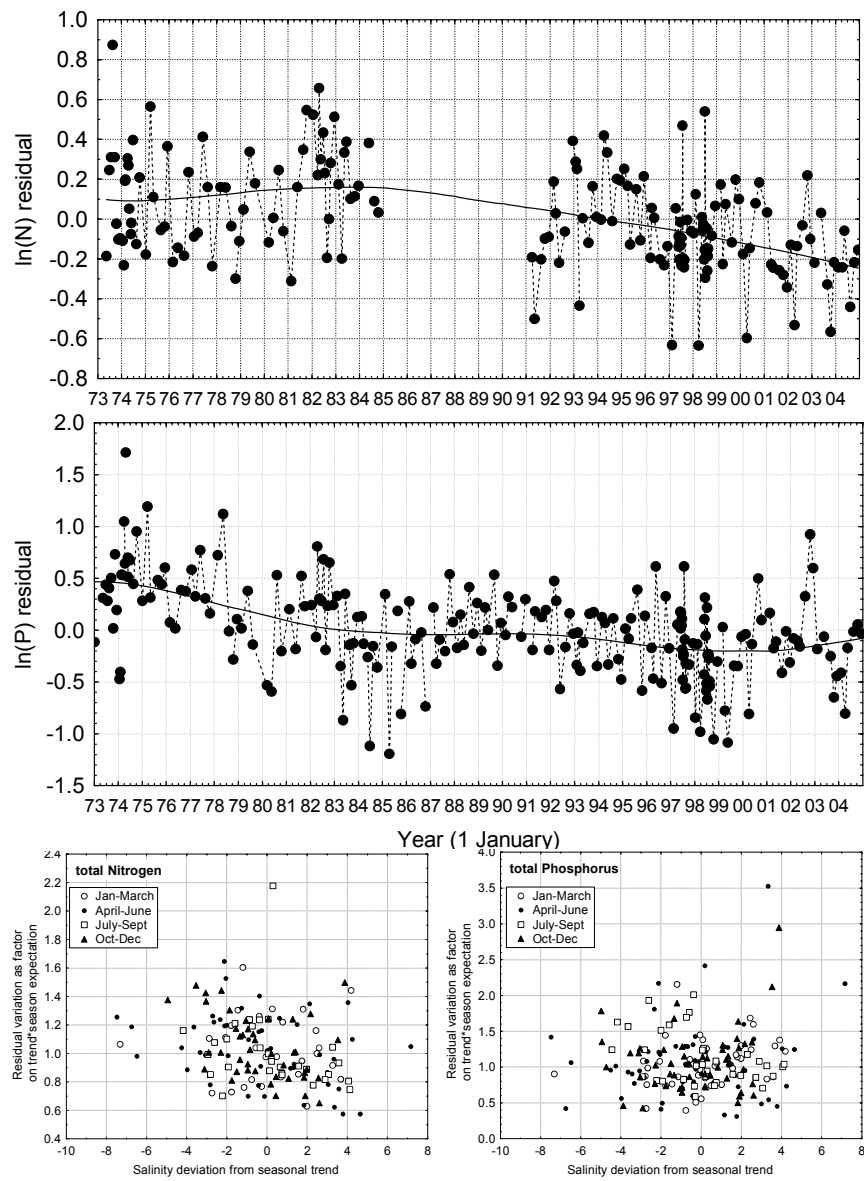


Fig. 2.8: Total nitrogen and total phosphorus residuals. Left pane: residuals from seasonal model on natural log-scale with nonlinear trend fit. Long-term expectation as function of salinity deviation from seasonal pattern (top and middle), stochastic variation relative to seasonal (lower). Observations are marked with different symbols according to season.

The plots indicate a negative correlation between the residual variation in total nitrogen and salinity, after correction for seasonal variation in both factors, and also correction for long-term trends in nitrogen, such a relationship is much less apparent for total phosphorus.

As a formal test of such a relationship, a covariance analysis of the residual factors of total nitrogen and phosphorus was performed. Salinity and temperature residuals around seasonal patterns were included as covariates, in interaction with month, and with month also as a main fac-

tor, to allow for different regression lines at different times of the year. This analysis will model $F_{residual}$ as a covariance function:

$$F_{residual} = \mu + \alpha_{Month} + \beta_{month} \cdot Sal_{dev} + \gamma_{month} \cdot Temp_{dev}$$

Months with very few data were excluded, so only data from February, April, May, August, October and December were included. The residual relative deviations in total nitrogen are related to covariates to some extent, while it is negligible for total phosphorus. The most important covariate is salinity deviation, and coefficients β_{month} for most months are around -0.04.

A simpler model with the same coefficients for all data has also been analysed:

$$F_{residual} = \mu + \beta \cdot Sal_{dev} + \gamma \cdot Temp_{dev}$$

The ANOVA table and estimated coefficients of both models are shown in Table 2.3. An incremental F-test on the significance of the improvement for total nitrogen by including separate slopes for individual months give $F(15,107)=1.0983$, which is not significant ($p=0.37$), so the simpler model with common slopes for all months appears to be sufficient. This model estimates coefficients ($\pm$ std. errors) $\beta=-0.035$ (± 0.0084) and $\gamma=-0.030$ (± 0.015).

Table 2.3: ANOVA table for covariate analyses on residual variation of total nitrogen and total phosphorus with deviations in temperature and salinity from seasonal pattern as covariates.

Effect		df	total Nitrogen			total Phosphorus		
			SS	MS	p	SS	MS	p
Separate slopes for each month.	Month	5	0.07	0.015	0.914	0.43	0.085	0.855
	Month*Temp _{dev}	6	0.82	0.14	0.017	2.34	0.39	0.109
	Month*Sal _{dev}	6	1.30	0.22	0.0006	1.31	0.22	0.432
	Error	107	5.38	0.050		23.43	0.22	
	Total	124	7.19	0.058		27.92	0.23	
	Variance reduction			13.3%			2.7%	
	Std.dev. reduction			6.9%			1.4%	
Overall p:					0.011			0.27
Common regression for all months	Temp _{dev}	1	0.21	0.21	0.042	0.03	0.03	0.699
	Sal _{dev}	1	0.89	0.89	<0.01	0.69	0.69	0.080
	Error	122	6.21	0.051		27.12	0.22	
	Total	124	7.19	0.058		27.92	0.23	
	Variance reduction			12.2%			1.3%	
	Std.dev. reduction			6.3%			0.6%	
Over-all p					0.00013			0.17

Thus, after adjusting for average seasonal pattern and long-term trend, the residual standard deviation in total nitrogen signal is reduced by between 6 and 7%, while there is no effect at all for phosphorus. Attempts to reduce residuals further by including meteorological variables as explanatory variables were unsuccessful, resulting in no further reduction of residual variation.

Chlorophyll as average of 0–4 m depth from June to August was regressed on Salinity, Water temperature and Cloud and Wind components, with the meteorological variables both for the observation date and the average over the previous two days. A backward stepwise regression selected clouds and southern wind as averages over the previous two days as the important covariates, with increased cloud cover and southern winds giving reduced chlorophyll values. The nominal overall p value of the final regression model is 0.0186, but since the step-wise regression is an exploratory method that considers many different models, this is not the real significance.

A randomisation test, where the stepwise regression was run repeatedly with the dependent variable reordered randomly within the data records at each run, showed that the real overall significance is 0.05. The covariate adjustment reduced the variance of chlorophyll by 32%, corresponding to a reduction by 17% of the standard deviation of chlorophyll. This model was based on only 19 observations, because temperature and salinity were missing for part of the data. Using only meteorological variables as covariates increased the number of available observations to 44.

Backward stepwise regression on these data gave air temperature of the previous two days as the only significant covariate, with increasing temperature giving reduced chlorophyll levels. The model would reduce standard deviations of chlorophyll by only 7%, and although the nominal p value was 0.0084, the randomisation test now showed a real p value of 0.2, which cannot be considered significant. The conclusion is that for these data, no clear relation between chlorophyll and physical covariates have been found.

Discussion

The attempts at reducing residual variation by correcting for covariates for these data have not led to any major improvements in the sensibility of indicators to detect differences or time trends. Only for total nitrogen is there a real, although minor improvement. The negative result may serve to show that one should be cautious in relying on covariate correction to improve statistical power when planning monitoring for classification of water bodies.

It seems reasonable to assume that irregular variation in surface nutrients around seasonal and long-term trends should be related to natural variations that might be caused by meteorological conditions and affect would also affect hydrophysical properties. However, it is by no means

obvious that relations would be simple monotonous relationships. In fact, different kind of events may give correlations in different directions. Salinity decrease in the surface layer may be caused by larger influx of freshwater or decreased vertical mixing, causing increase or decrease of surface total nitrogen or phosphorus, respectively.

Freshwater influence to the inner Oslofjord may be caused by local rainfall or snow melting, or come from the major rivers that affect the outer fjord with peaks at different times. River runoff during flood will have different concentrations of nutrients at different stages during a flood peak, and the same may apply to surface water in the fjord for different stages of an episode with decreasing salinity, for instance.

Wind will cause both vertical mixing and horizontal movements of water, and in different ways depending on wind direction. The interaction between short-term events and seasonal development may give different combined effect at different times, so that reliable, consistent relationships are difficult to find. It is reasonable that total phosphorus show no relation at all, while there is a certain consistent covariate correlation with nitrogen. Phosphorus is more bound to particles, and much more variable in river runoff than nitrogen, in particular in connection with flood peaks. Similar considerations apply to chlorophyll, which in addition is very variable due to biological fluctuations.

Thus, it may be disappointing, but perhaps not surprising, that it is difficult to find clear correlations between eutrophication indicators and hydrophysical or meteorological conditions for this area.

Conclusion

Analysis of surface nutrient data from the inner Oslofjord indicate that short-term variations around seasonal patterns and long-term trends in nutrient concentrations in the surface layer cannot be corrected to any large extent by using physical covariates. Only for total nitrogen was a significant correlation found, with a weak increasing trend for decreasing salinities and decreasing temperatures, correcting for this correlation may improve the sensitivity of statistical tests by 6% in terms of the size of the trend that may be detected by a given monitoring program, or the precision by which a water body may be classified. For phosphorus no improvement was seen, and for chlorophyll, the data are too sparse and variable to assess covariate correlations.

2.5.2 Askö example

Introduction

The response variables: The analysis of covariate correction at the Askö station (Fig. 2.9) was focused on the response variables Secchi depth, chlorophyll-A (ChlA), total nitrogen (TN) and total phosphorous (TP). Secchi depth was studied since it is frequently used as a general indicator

of coastal water quality. It is also one of the very few water quality variables where historical records are reliable since it is estimated in essentially the same way today as when the method was presented by Angelo Secchi in 1866. For most chemical analyses historical comparisons are difficult because of development in analytical methods and differences between labs. Secchi depth has often been shown to be a good overall descriptor of water quality related to biological production and emissions of biodegradable material. ChlA reflects the biomass of phytoplankton and thus potentially detects increased production caused by external nutrient load. The effect of covariates on total nitrogen was studied since TN during the winter period reflects the nitrogen store in the water mass and the summer increase in TN has recently been shown to reflect the extent of nitrogen fixation performed by filamentous cyanobacteria in the Baltic. The amounts of nitrogen added to the system by this process are considerable (estimated to approximately one third of total nitrogen load) and contribute to the eutrophication process. The magnitude of cyanobacterial blooms in the Baltic appears to be increasing and it is therefore highly desirable to identify trends in TN increase. Total phosphorous reflects the store in the water mass and the availability of phosphorous is considered to regulate cyanobacterial growth.

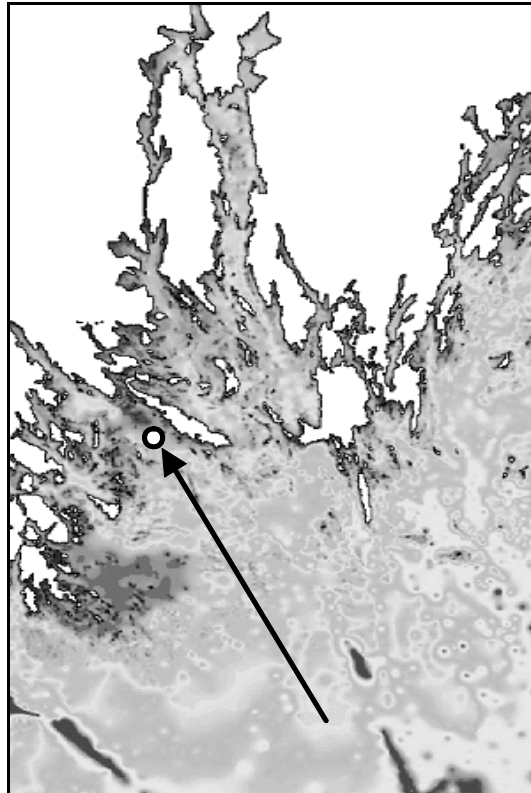


Fig 2.9: The Askö station is located in the archipelago south of Stockholm.

The seasonal cycle at the station: The station is located in an area with pronounced seasonal variation in temperature and production cycle and is often covered by ice from December to March. The warm winters prevailing since 1990 have however made permanent ice cover during winter rarer. The surface salinity at the station varies between 5.5 and 7.9 PSU with the minimum in the summer months (Fig 2.10). At the sediment salinity is generally between 6 and 8.5.

During summer a pycnocline develops between 15 and 20 meters. The spring bloom takes place in March to early May depending on the ice situation and generally peaks in late March or early April. It is dominated by diatoms and dinoflagellates and drains the surface water of dissolved inorganic nitrogen but some phosphate is generally left in the surface water.

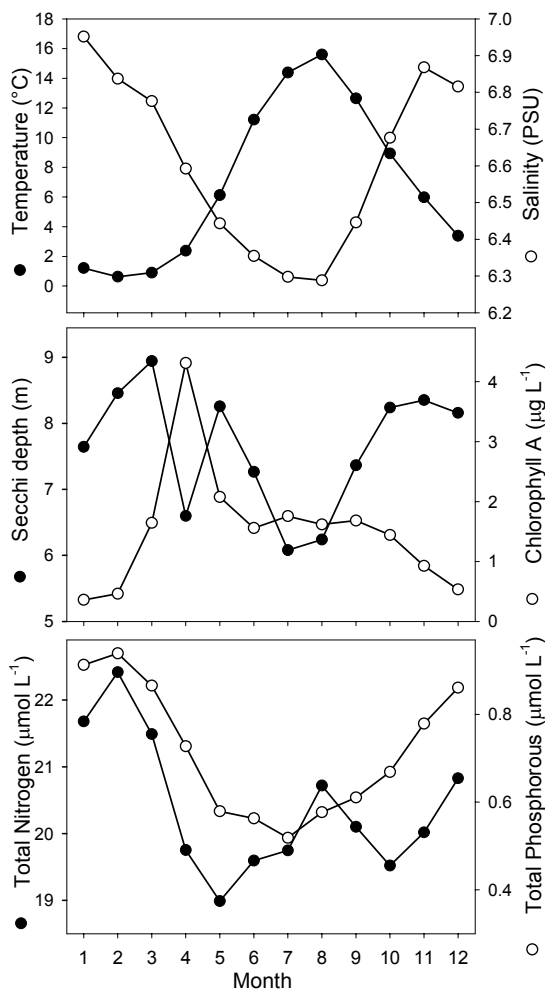


Fig 2.10: Monthly averages of temperature, salinity, Secchi depth, ChlA, total nitrogen and total phosphorous at the Askö station. Averages for 0, 5, 10 and 15 meters.

The spring bloom causes a clear decrease in Secchi depth and after the spring bloom sedimentation the Secchi depth temporarily increases by ~2 meters before the summer community of cyanobacteria and dinoflagellates appears. During summer Secchi depth decreases to reach a minimum in July to August coinciding with the maximum temperatures but with no apparent connection to the ChlA levels. Surface temperature reaches a maximum coinciding with a salinity minimum in the summer months.

ChlA shows a pronounced peak in April in connection with the spring bloom (Fig. 2.10). After the spring bloom ChlA decreases and shows little variation during summer. TP shows little variation in the winter months December to March but decreases continuously after March to reach a minimum during the summer months. TN shows a similar pattern but from May to August TN increases as a result of cyanobacterial nitrogen fixation.

The covariates: Covariates tested for adjustment of yearly means were temperature, salinity and wind. The Askö station is located at an open coastal site with no major outflow of fresh water. Water with lower salinity however reaches the station when surface water from the Bothnian Sea mixes with the water from the Baltic Proper. The station is sheltered by land from moderate northerly winds but at higher wind speeds northerly winds cause upwelling. Southerly winds of medium strength and short duration cause inflow of surface water from the open Baltic whereas strong and long lasting southerly winds may cause upwelling by Ekman transport. The depth is 42 meters at the station but further out trenches of greater depth allows transport of deep water from the open Baltic at storm events (Fig. 2.9). Salinity, temperature and wind are therefore likely external covariates that may introduce short-term residual variation in trends of response variables. The logarithm of ChlA has been tested as an internal covariate to reveal its degree of covariation with the other response variables but was not used as correction for means, since it is an internal variable.

Materials and methods

The covariation of the variables Secchi depth, ChlA, TN and TP with temperature, salinity and wind speed was made by standard covariance analysis (ANCOVA). The general model for ANCOVA is:

$$Y_{ij} = \mu + \alpha_i + \beta_{\text{within}} (X_{ij} - \bar{X}_i) + \varepsilon_{ij}$$

Where Y_{ij} is the j th observation of the i th year, α_i is the deviation of the i th year from the grand mean of observations, $\beta(X_{ij} - \bar{X}_i)$ is the effect explained by the difference of the covariate from its mean and ε_{ij} is the random variation (See also Section 2.1). In the analysis presented here the inclusion of more than one covariate was never justified by increase

in precision and the simplest model of correction with one covariate was therefore always used. The effect of ANCOVA correction was estimated as change in residual standard error (RSE), the square root of residual mean square.

Because of the pronounced seasonality sampling was made with higher frequency during spring and summer (weekly to biweekly) than during winter and fall (biweekly to monthly). Therefore no seasonal correction was made to avoid different power in the analysis caused by the differences in data density and since non-modelled seasonal biological processes (particularly production) are known to strongly affect the response variables. To avoid confounding of seasonal variation in the covariate with residual variation caused by short-term variation, different periods of the year were chosen for the different covariates. The periods were chosen by the criteria that the response variable should be likely to show information relevant to load situation rather than internal biological processing during the period, little seasonal variation should occur in either the observed response variable and its covariates and that the periods included as much and as balanced data as possible without violating either of the other conditions. Three periods were considered: Winter period (day 1–100 i.e. 1 Jan – 10 April), spring bloom (day 64–130, 5 March – 10 May) and summer bloom period (day 149–249, 29 May – 6 September). Annual means of Secchi depth and ChlA were analyzed for the spring bloom and summer periods whereas TN and TP were analyzed for the winter and summer periods. Secchi depth and ChlA are strongly affected by spring bloom and are during this period likely to reflect the production and biomass of phytoplankton. During summer Secchi depth decreases to a minimum and ChlA shows small variation between months (see also Discussion). TN and TP are most representative of load during the winter period since they are strongly affected by the sedimentation of the spring bloom. Before sedimentation the spring bloom itself can mainly be seen as a transfer from the inorganic nutrient pool to the organic, which are both included in TN and TP. The seasonal changes in both TN and TP are therefore small during the period, as are the fluctuations in temperature and salinity. During the summer TN increases from a minimum in May to a summer maximum in August whereas TP reaches a broad minimum in same period. The rationales for the choice of analyzed periods for each variable are treated further in Discussion.

The open coastal position of the station makes wind a likely cause for variation (see Introduction). The speed and direction of the wind was measured by the Swedish Meteorological and Hydrological Institute (SMHI) at Landsort ~9 nm SE of the station with 3 h intervals. Wind effect was calculated in three ways. To account for the wind speed independent of direction the average wind during 12 and 24 hours preceding the sampling was calculated. To account for the effect of wind direction in relation to the position of the station, each speed observation was mul-

multiplied by -1 for northerly winds (270° to 90°) and by $+1$ for southerly winds (91° to $+269^\circ$) and then summed.

Temperature, salinity, Secchi depth and ChlA have been measured 19–25 times per year since 1982 and TN and TP have been measured with the same frequency since 1996. The analysis of Secchi depth and ChlA is therefore based on data from 1982–2004 whereas analyses of TP and TN are based on data from the period 1996–2004. For each sampling occasion the average value of the depths 0, 5, 10 and 15 have been calculated and used as individual observations in the analysis.

Results

In all analyses temperature and salinity have been included but the three different estimates of wind effect were only introduced one at the time to avoid autocorrelation effects. In no case was any estimate of wind effect a significant covariate and in no case did inclusion of more than one covariate affect the residual SE more than marginally. All corrections are therefore made with the simplest model of one covariate (see Methods). The adjusted means were calculated as the yearly means expected in the response variable had the covariate had been at its overall mean value. Results are only reported where significant covariation ($P < 0.01$) was found (Table 2.4).

Table 2.4: Parameter estimates for ANCOVA regression of significant covariates for different response variables.

Variable	Days	Covariate	Slope	SE	t	df	P
Secchi depth	64–130	log(Chl A)	-3.86	0.33	-11.6	129	<0.001
Secchi depth	149–249	Temp	-0.26	0.032	-7.9	137	<0.001
Chlorophyll A	149–249	Salinity	-2.18	0.32	-7.0	136	<0.001
TN	149–249	Temp	0.28	0.040	-6.9	53	<0.001
TP	1–100	Salinity	0.45	0.073	6.1	43	<0.001

Secchi depth: Secchi depth was found to co-vary strongly and negatively with log(ChlA) during the spring bloom. The improvement of the RSE was from 1.81 to 1.27 m (-30%) and $R^2=0.51$. The results show that Secchi depth is heavily dependent on ChlA during the spring bloom. No correction was however made since ChlA is an internal variable reflected in Secchi depth. In the summer period Secchi depth showed a clear negative relationship with temperature (Table 2.4, Fig. 2.11) but not with log(ChlA). The improvement of RSE was from 1.32 to 1.09 m (-17%) and $R^2=0.32$. The range of differences between uncorrected and corrected means was from -0.5 to $+0.6$ m (-8.2% to 10%).

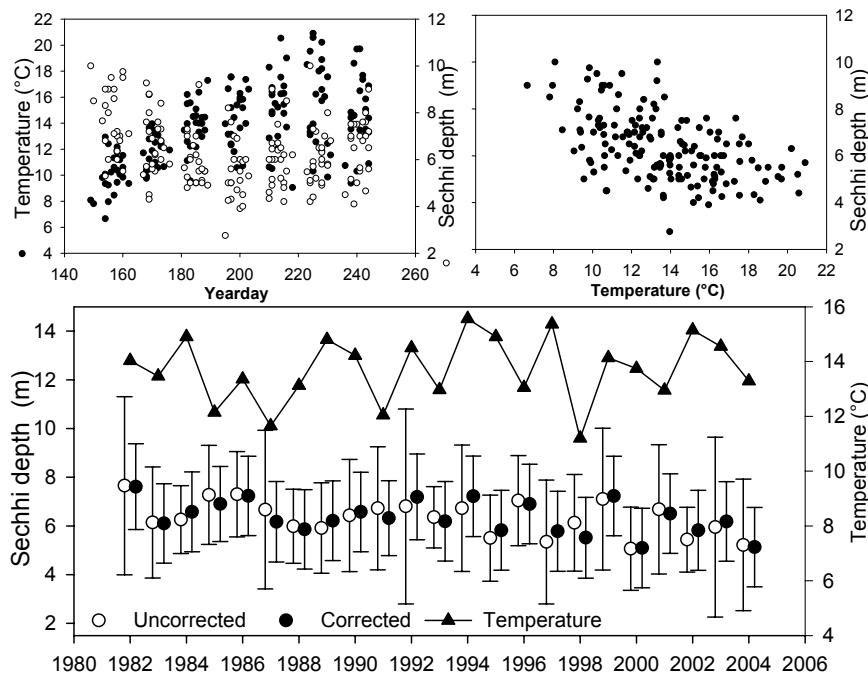


Fig 2.11: Covariation between summer temperature and Secchi depth, day 149–249 for the years 1982–2003. Upper left panel: temperature (left scale ●) and Secchi depth (right scale ○) by yearday. Upper right panel: phase plot of temperature and Secchi depth. Lower panel: average summer temperature and uncorrected and corrected summer Secchi depths by year.

ChlA (ChlA): ChlA covaried negatively with salinity both during spring bloom and the summer period. For the spring bloom period the effect of correcting logarithmic means of ChlA was marginal. The summer correction (Table 2.4, Fig. 2.12) was made on non-logged data since the variation in the period is generally low (Fig. 2.10, Fig. 2.12). Improvement of RSE was from 0.64 to 0.55 (-13%) and $R^2=0.26$. Differences between uncorrected and corrected means ranged from -0.92 to $+0.77 \mu\text{g l}^{-1}$. Since some values were close to zero, the range of mean differences expressed in percent was very large and is misleading (-81% to +51%).

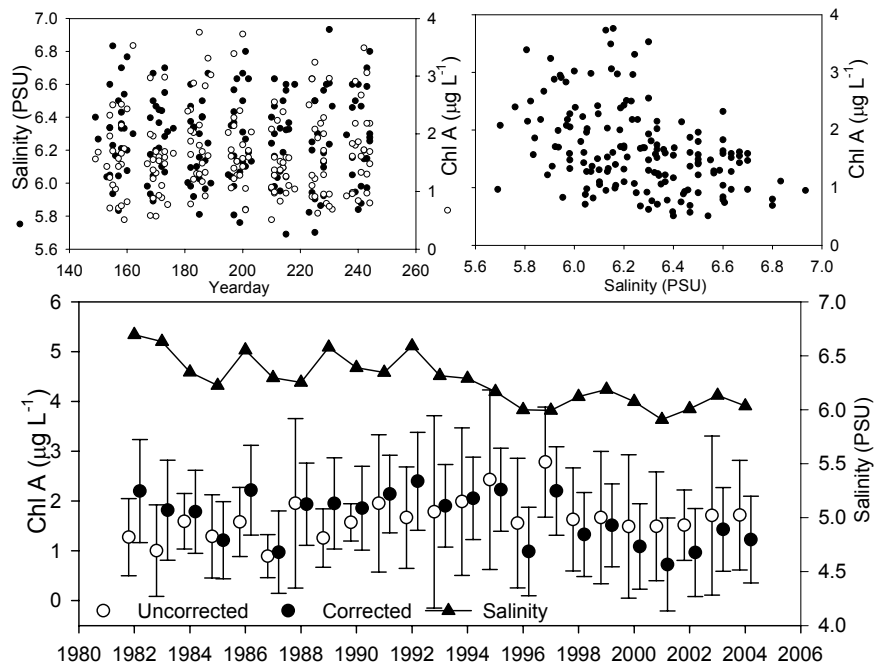


Fig 2.12: Covariation between summer salinity and chlorophyll-A, day 149–249 for the years 1982–2003. Upper left panel: salinity (left scale ●) and chlorophyll-A (right scale ○) by yearday. Upper right panel: phase plot of salinity and chlorophyll-A. Lower panel: average summer salinity and uncorrected and corrected summer chlorophyll-A by year.

Total nitrogen (TN): TN showed significant covariation with $\log(\text{ChlA})$ during the winter period but the effect on RSE was relatively small (-9%) and no adjustment was attempted since ChlA is an internal variable. During the summer period TN covaried positively with temperature (Table 2.4, Fig. 2.13). Improvement of RSE was from 1.30 to $0.94 \mu\text{mol l}^{-1}$ (-27%) and $R^2=0.47$. The range of differences between uncorrected and corrected means was from -0.69 to $0.46 \mu\text{mol l}^{-1}$ (-3.6% to +2.1%). The relationship is likely to be caused by cyanobacterial nitrogen fixation (See Discussion).

Total phosphorous (TP): TP covaried weakly with salinity during the summer period but the effect on RSE was marginal (-3%). For the winter period the covariation with salinity was considerable (Table 2.4, Fig. 2.14). The improvement of RSE was from 0.087 to $0.064 \mu\text{mol l}^{-1}$ (-26%) and $R^2=0.47$. Differences in means ranged from -0.21 to $+0.23 \mu\text{mol l}^{-1}$ (-30% to +23%).

Discussion

The results show that correction for covariation with salinity and temperature can increase the precision in monitoring data of Secchi depth, ChlA, TN and TP. The precision increase, estimated as change in RSE, was between -17% and -30%. The station is in a mixing zone of water, which makes it unlikely to find very strong covariates. The area may

depending on wind and runoff receive water from the Bothnian Sea, Southern Baltic proper or the Gulf of Finland as well as deep water from the western Baltic proper. It must also be seriously stressed that at a location with strong seasonality high frequency sampling is the only reliable way of detecting differences between years with high precision.

The different seasonal density in data and the dramatic seasonality motivated the division of the analysis into periods rather than a general seasonal correction. Since the major environmental concern in the area is eutrophication the periods analysed were selected with the intention of deriving information on eutrophication from the response variables. During the winter Secchi depth and ChlA hold little information since the biomass is very low.

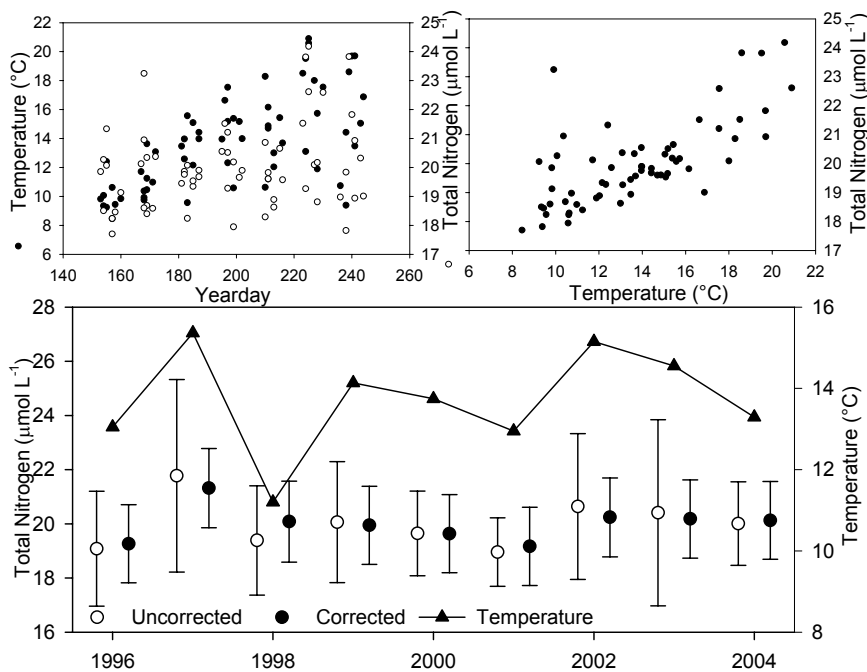


Fig 2.13: Covariation between summer temperature and TN, day 149–249 for the years 1996–2003. Upper left panel: temperature (left scale ●) and TN (right scale ○) by year-day. Upper right panel: phase plot of temperature and TN. Lower panel: average summer temperature and uncorrected and corrected summer TN by year.

TN and TP are in contrast during winter likely to be most representative for the store of nutrients. The spring bloom affects Secchi depth and ChlA dramatically and they may at this period be good estimators of eutrophication effects on production. The occurrence in time of the spring bloom is however highly variable in a weekly time perspective. If the peak occurs between two sampling occasions the yearly average may be considerably affected. Sampling is therefore performed weekly during this period.

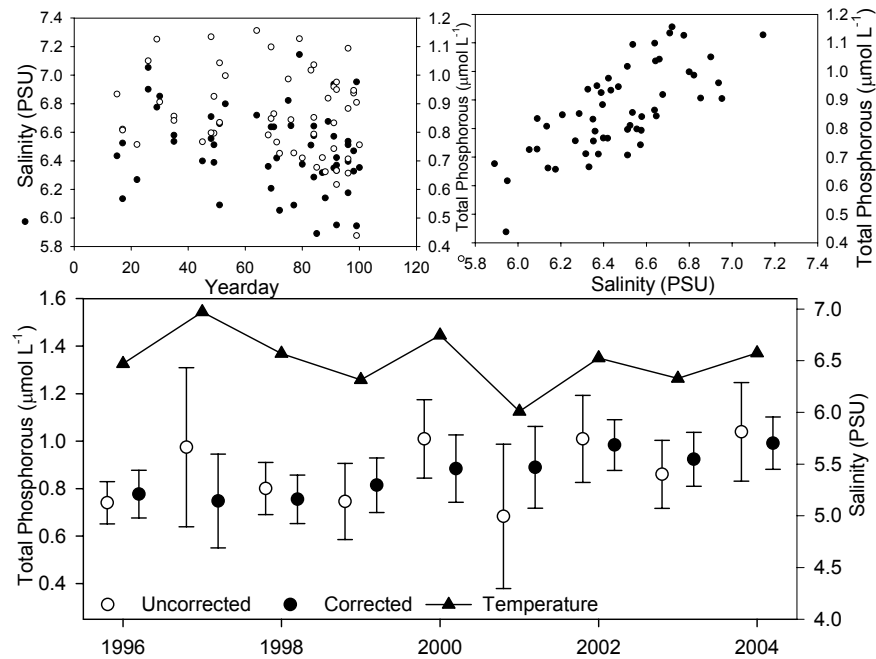


Fig 2.14: Covariation between winter salinity and TP, day 1–100 for the years 1996–2003. Upper left panel: salinity (left scale ●) and TP (right scale ○) by year/day. Upper right panel: phase plot of salinity and TP. Lower panel: average winter salinity and uncorrected and corrected winter TP by year.

Secchi depth reaches a minimum during summer, when the sea is used intensely for recreational purposes. Summer Secchi depth is thus often a water quality indicator of considerable interest to the public. The historical comparability and generality of the Secchi depth method makes it a scientifically highly useful variable, which often reflects production level. In contrast to Secchi depth, ChlA remains relatively constant since the production system is characterized by recirculation with low biomass but high production.

Since nitrogen fixation has been found to be a major contributor to eutrophication, TN and TP are relevant during this period since TN increases drastically and TP reaches its minimum. The correction of TN is therefore more a correction of variations in a process rather than a state. A problem in the analysis of the summer period is that the covariate temperature also increases significantly during this period. Temperature correction of Secchi depth and TN should during this period perhaps be more seen as an adjustment for the timing of sampling in relation to the temperature development, than an increase in precision of a state characterization.

Secchi depth: The effect of $\log(\text{ChlA})$ on Secchi depth during spring bloom shows the strong interdependence between the two variables in the period but no such dependence was found during summer. During summer Secchi depth instead covaried strongly with temperature. The causes

for this relationship are not entirely clear but a likely explanation is that the covariation in temperature reflects the TN concentration, which was found to be positively dependent on temperature. TN is affected by the summer nitrogen fixation, which may in turn affect the production and potentially the species composition during summer. The lack of covariation with ChlA however suggests that the relationship is not a result of phytoplankton biomass accumulation.

ChlA: The covariation of ChlA with salinity during summer is most likely caused by water transport. Both variables undergo small changes in the period and the correction is likely to increase the precision of a characteristic annual ChlA concentration in summer. It is worth observing that salinity has decreased in the surface water since 1990, which is most likely caused by high annual precipitation since mid 1980. The correction may therefore be appropriate to use as a correction for long-term change.

Total nitrogen (TN): The strong covariation between temperature and TN is most likely caused by cyanobacterial nitrogen fixation. The main nitrogen fixing species are *Nodularia spumigena* and *Aphanizomenon sp.* Both species have higher temperature optima than most other primary producers and are therefore assumed to be dependent on warm summers and a strongly stratified water column to develop large blooms. The relation was particularly pronounced for the months July and August when temperature peaks and TN reaches a local maximum. In contrast to TN, the sedimentation and lack of input causes the TP concentration to reach a minimum during this period. During other parts of the year there is no clear covariation between temperature and TN. The same covariation with temperature was found at the open sea monitoring station at Landsort.

Total phosphorous (TP): There is no clear explanation to the covariation between salinity and TP during the winter period. The relation was found to be valid for all months except for the summer months but no correction was made using all data since the seasonal variation in salinity was considered too large. If the data from the entire year was included the ANCOVA regression was highly significant with $R^2=0.67$ and the decrease in RSE was 68%. This is however to large extent explained by similar seasonal variation (Fig. 2.10). A potential explanation is upwelling of water that has been in contact with the sediments. The TP concentration is higher in water overlying the sediments than in the surface water. The concentration difference between surface and deep water was however most pronounced in summer and early autumn when the relation between salinity and TP was weakest. A more likely explanation is therefore that wind induced transport of water causes wave action increasing the amount of particles in the water, which in turn may cause an increase in TP since the analysis is made on unfiltered water.

The result that none of the used estimates of wind effect could be used as a covariate was unexpected, considering the open coastal position of

the station. For the summer period upwelling events were identified individually by rapid drops in temperature. At these events Secchi depth increased and ChlA levels decreased. Annual averages of biological variables for a given coastal station are likely to be more representative if such occasions are excluded. The events were however too few to affect a linear model including all seasonal data. In the winter period only very large upwelling events can be detected since the salinity and temperature differences are small.

Conclusions

Covariate correction increased precision on seasonal data of biologically relevant monitoring variables at the Askö station. For an open station like this, where the water transport is complex the causality for covariation is however complex. There is thus a greater risk of removing essential information by correcting for covariates than at stations that have clearer forcing conditions (e.g. bays with fresh water outflow or recipients with clear point sources).

2.5.3 Laajalahti and Vanhankaupunginlahti Bay example

Introduction

Laajalahti and Vanhankaupunginlahti are semi-enclosed inner bays of Helsinki City. They are characterized by restricted water exchange with the open Gulf of Finland due to narrow sounds. The estuaries are shallow (mean depth ca. 5 m) and small in size (surface areas 5.3 km² and 5.5 km²). They differ from each other in terms of watershed, fresh water input and residence time. Laajalahti receives fresh water mainly from two small brooks (drainage areas altogether 43.4 km²), whereas Vanhankaupunginlahti is strongly affected by the River Vantaa (drainage area 1686 km², MQ 16.4 m s⁻¹). The theoretical residence times of Laajalahti and Vanhankaupunginlahti are 0.011 and 0.28 years, respectively. The local municipal treatment plants in both of the estuaries were closed in the late 1980s.

The aim of this analysis was to identify indicator of water quality in two estuaries off Helsinki and to attempt to reduce the variability in these indicators by taking into account variability in physical forcing variables (water flow, salinity, temperature and wind speed) and the internal variables (e.g. the dependency of Secchi depth and the concentrations of chlorophyll *a*). The data sets were studied to test a hypothesis that salinity is the main external forcing factor determining the annual average values of different water quality indicators in Vanhankaupunginlahti due to the influence of the River Vantaa. Wind and temperature are hypothesized to be included in the driving forces in both of these shallow bays.

Materials and methods

The water quality data of Laajalahti and Vanhankaupunginselkä originates from the local monitoring program of Helsinki City in 1989–2004 and are stored in the register of the Finnish Environment Administration. Water quality samples of secchi depth, salinity, total phosphorus, total nitrogen and chlorophyll *a* were usually taken 11 to 19 times per year from two sampling stations, one located in Laajalahti in the western side of Helsinki and the other in Vanhankaupunginlahti in the eastern side of the City. Daily water flow of the River Vantaa originated from the hydrological database of the Finnish Environment Institute. Daily observations on wind speed originated from the Finnish Meteorological Institute.

In co-variation analyses, the annual average Secchi depth (SD), and the annual average concentrations of chlorophyll *a* (CHL*a*), total phosphorus (TP) and total nitrogen (TN) in the water column were tested as indicators of water quality; weekly water flow of the River Vantaa, the average salinity and temperature in the water column and wind speed as physical forcing variables; and the average concentrations of chlorophyll *a* in the water column as an internal variable in Laajalahti and Vanhankaupunginselkä. All the variables were measured at sampling time. Only open water period between April and November were included in the analyses of Secchi depth and CHL*a* as the water is ice-covered in winter. All the variables except Secchi were log-transformed to stabilize variance, as they were not normally distributed.

A series of linear models were tested to find significant relationships between indicators and physical forcing variables individually and in combination. The models were run using the General Linear Models (GLM) procedure in the SAS software package. As a part of the analyses the model parameters were tested to see if they varied significantly between years and months. The idea of these analyses was described in detail in the general introduction of this report.

Results

Laajalahti

In Laajalahti, *Secchi depth* was on average 0.9 m, ranging from 0.4 to 2.2 m. The model combining the annual and seasonal variations accounted for 53% of the variation in Secchi depth. Salinity was the only significant driving force in the model, as neither wind nor temperature could be linked to the variations of Secchi depths. The model including salinity accounted for 59% of the variation in Secchi depth. However, the standard error of the residuals of these models were only marginally improved (root MSE = 0.175 and 0.169). Model coefficients are presented Appendix Table A.1.

$$SD = I_0 + K_S * \text{Salinity}, R^2 = 0.60$$

The concentrations of *total phosphorus* averaged $54 \mu\text{g l}^{-1}$ and varied from 23 to $130 \mu\text{g l}^{-1}$. The best model was gained on seasonal basis, as salinity did not improve the coefficient of determination ($R^2 = 0.77$ and 0.78), nor the standard error of the residuals (both $\text{MSE} = 0.079$). The parameter estimates of the model were acceptable between May and October (Appendix Table A.2).

$$\log\text{TP} = I_0 + K_{\text{TP}} * \text{Salinity}, R^2 = 0.78$$

The concentrations of *total nitrogen* were on average $756 \mu\text{g l}^{-1}$, varying from 440 to $1\,895 \mu\text{g l}^{-1}$. The model combining annual and seasonal variation was responsible for the main part of the variation in the annual average TN ($R^2 = 0.66$). Salinity was the only external variable to be included in the model. This model explained 71% of the variation in the annual average TN, the parameter estimates being significant ($\text{ProbT} < 0.05$) only in January to March and in May to June. The model including salinity improved the standard error of residuals by 10% (root MSE were 0.079 and 0.072, respectively). The parameter estimates of the model were acceptable between January and March and between May and June (Appendix Table A.3).

$$\log\text{TN} = I_0 + K_{\text{TN}} * \text{Salinity}, R^2 = 0.71$$

The concentrations of *chlorophyll a* were on average $24 \mu\text{g l}^{-1}$, ranging from 2.1 to $160 \mu\text{g l}^{-1}$. CHLa could be linked to salinity in May and June, but this model did not improve predictions ($R^2 = 0.39$) compared to the model including annual and seasonal variations ($R^2 = 0.36$), nor reduce the standard error of residual (root MSE = 0.14 in both of the models).

Vanhankaupunginlahti

In Vanhankaupunginlahti, the annual *Secchi depth* was on average 0.5 m, the values ranging from 0.1 to 1.2 m. The prediction including annual and seasonal variation ($R^2 = 0.24$) improved when combining the weekly water flow of the River Vantaa ($R^2 = 0.67$) as an external forcing variable into Secchi model. There was considerable improvement of the standard error of residuals (root MSE 0.26 and 0.17, respectively), but the parameter estimates were not acceptable during the open water period. Model coefficients are presented in Appendix Table A.4.

The concentrations of *total phosphorus* averaged $87 \mu\text{g l}^{-1}$ varying from 29 to $315 \mu\text{g l}^{-1}$. The model combining annual and seasonal variation accounted for 27% of the variation in the annual TP. The model including salinity predicted 56% of the variation, but showed acceptable parameter estimates ($\text{ProbT} < 0.05$) only for winter months (January to March). The standard error of residuals was improved by almost 20% (root MSE = 0.16 and 0.13 respectively).

The concentrations of *total nitrogen* averaged $1840 \mu\text{g l}^{-1}$ varying from 510 to $4\,950 \mu\text{g l}^{-1}$. The model combining annual and seasonal variation accounted for 52% of the variation in the annual TN. R^2 improved to 0.76, when linking salinity into the model. There was only a small change between standard error of residuals (root MSE = 0.17 and 0.13 respectively). Model coefficients are presented in Appendix Table A.5.

$$\log\text{TN} = I_0 + K_{\text{TN}} * \text{Salinity}, R^2 = 0.76$$

The concentrations of *chlorophyll a* were on average $29 \mu\text{g l}^{-1}$ varying from 0.5 to $115 \mu\text{g l}^{-1}$. The model taking into account only the annual and seasonal variations was responsible for the main part of the variation (r-square 0.53). Salinity was the only external forcing factor that could be associated with the predictions of the annual average CHLa. This model accounted for 61% of the variation of the annual average CHLa. There were practically no reduction in the standard error of residuals (root MSE = 0.32 and 0.33 respectively). Model coefficients are presented in Appendix Table A.6.

$$\log\text{CHLa} = I_0 + K_{\text{CHLa}} * \text{Salinity}, R^2 = 0.61$$

Discussion

Laajalahti and Vanhankaupunginlahti represent coastal water areas characterized by great seasonal variations due to meteorological and hydrological conditions in the northern Baltic Sea. For example seasonal variation of water temperature is considerable (0 to 20°C) and the water is ice-covered during winter. The innermost coastal waters of Finland are also strongly affected by the seasonality of hydrological conditions (Fig. 2.15). In this light, it may not be surprising that seasonal variations generally explained the main part of the variations in the annual average values of the studied indicators and external forcing factor such as salinity only had a marginal additional effect.

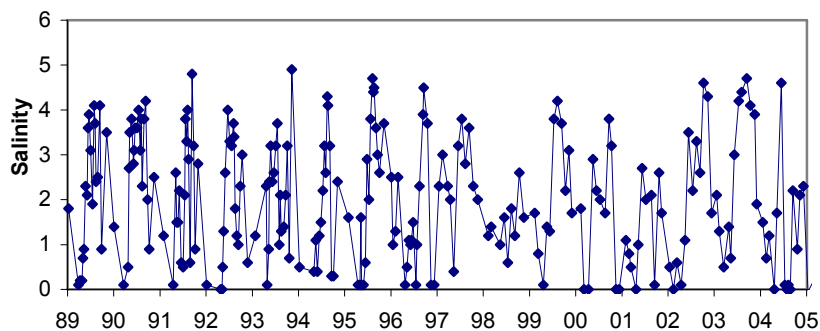


Fig 2.15: Variation of salinity in Vanhankaupunginlahti in 1989-2005.

Salinity was actually the only external factor that could be associated with the predictions. A typical pattern was, however, that despite the improvement in the coefficients of determination in the models including salinity, there was practically no reduction in the standard error of residuals. Thus, the effect of salinity was not as clear as expected. One explanation may be the small salinity ranges in the studied estuaries.

Internal loading both in Laajalahti and Vanhankaupunginlahti is one reason why salinity did not improve much the predictions of TP and chlorophyll *a*. Especially Laajalahti is strongly affected by release of P from the sediment, which is not dependent on salinity. All extra P can be bound to phytoplankton biomass, as phytoplankton primary production is N limited. This explains why salinity, which can be considered as a measure of nutrients from the coast and from the open sea, did not link with chlorophyll *a*.

No model combining water flow from the River Vantaa could be developed in Vanhankaupunginselkä, although the river has been shown to control water transparency and trophic conditions in the inner coastal areas off Helsinki (Autio et al. 2003). According to Korpinen et al. (2001), high concentrations of suspended solids in the River Vantaa limit the growth of phytoplankton in the coastal water area affected by the river water. As a consequence, the nutrient load carried by the river has time to be carried to an extensive coastal water area before phytoplankton utilizes nutrients for their growth.

Finnish estuaries and coastal waters are shown to be wind sensitive (Kauppila et al. 2001). Thus, it was odd that wind speed could not be linked to the annual average values of the studied indicators in these shallow estuaries. One explanation could be that at least in Vanhankaupunginlahti the fresh-water inflow from the River Vantaa is probably a much greater power than wind in contributing resuspension of nutrients through mixing of the water column. Besides that, wind conditions in these bays did not necessarily correlate with those in the outer archipelago, where the wind data actually came from.

One would think that temperature would be included in the external forcing factors in Laajalahti, as the release of P from the sediment is dependent on temperature (Holdren and Armstrong 1980, Kelderman and Van der Repe 1982), and internal loading is the main source of nutrients into the bay (Kauppila et al. 2005). However, the effect of temperature was probably already included in the models taking into account seasonal variations. However, considering temperature in Laajalahti only in summer conditions, its effect is evident (Vascetta et al. 2005, submitted).

2.5.4 Moonsund example

Introduction

The Vāinameri (Moonsund) and Gulf of Riga form a semi-enclosed sea basin in the eastern Baltic Sea bordering with Estonia and Latvia and having relatively narrow connections through straits with the open Baltic Proper (Fig. 2.16). The main factors affecting the water quality in the basin are the water exchange through the straits connecting the basin with the open Baltic Sea and the river runoff into the basin. The area and the volume of the Vāinameri and Gulf of Riga are $1.9 \cdot 10^{10} \text{ m}^2$ and $4.1 \cdot 10^{11} \text{ m}^3$ respectively. The basin reaches its maximum depth of 50 m in the center of the Gulf of Riga. The annual river runoff into the basin is about $5 \cdot 10^{10} \text{ m}^3$.

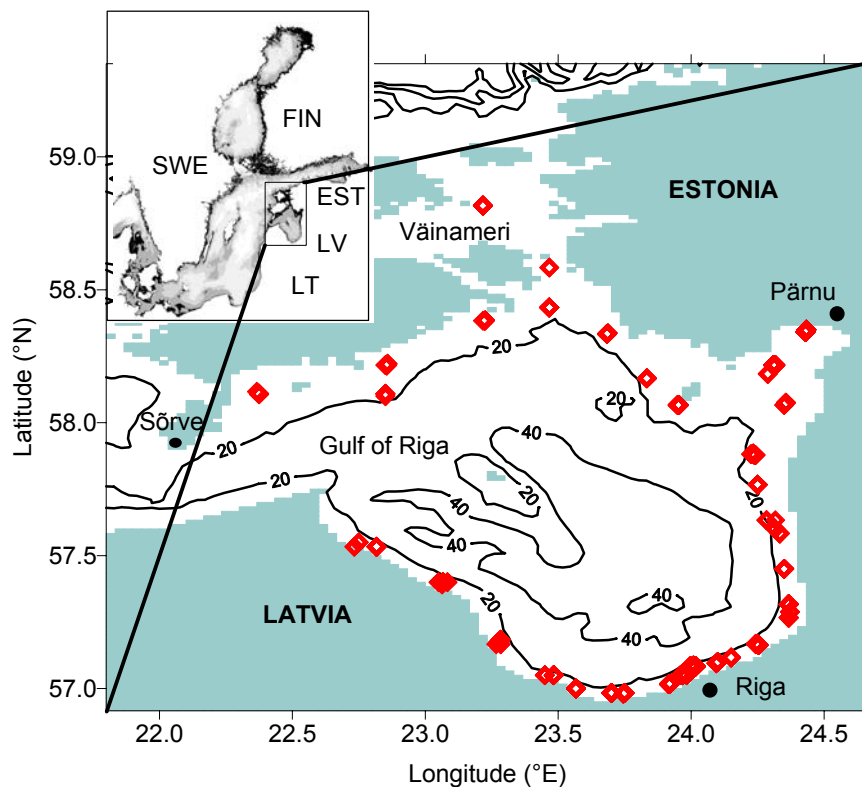


Fig 2.16 Outline of Vāinameri and Gulf of Riga with 20m and 40m depth isolines and the location of measurements of TotN (open diamonds) analyzed in the report. The analysis is aimed to identify water quality indicators (TotN), to find out their degree of covariance and, if possible, to reduce the variability by accounting for the co-variation of external forcing (wind speed) and/or internal co-variates (salinity).

Data

The data utilized in the analysis were downloaded from the Baltic Environmental Database (BED) at the Stockholm University (<http://data.ecology.su.se/models/>) and comprised the measured temperature (TEMP), concentrations of salinity (SALIN), oxygen (OXY), phosphate (PO4P), total phosphorus (TOTP), silica (SIO4), nitrate (NO3N), nitrite

(NO₂N), sum of nitrate and nitrite (NO₃N), ammonia (NH₄N), total nitrogen (TOTN) and chlorophyll-a (CHL) from the area with longitudes 21.8 to 24.6 °N and latitudes 56.9 to 59.3 °E belonging to the years 1980 to 1998.

Results

The cross-correlation coefficients and their significance were estimated for all listed variables (Table 2.5). The non-significant ($p > 0.01$) correlations are denoted by shaded cells in Table 2.5 and the significant correlation coefficients exceeding by the absolute value or equal to 0.6 are written in bold. High significant ($p < 0.01$) correlation coefficient values were found between the variable pairs NO₃N- SIO₄, TOTN- SALIN, CHL- SALIN, CHL-OXY, CHL- TOTN. Wind as an external covariate is also significantly, though weaker, correlated with SIO₄, TOTN and CHL. Therefore it was considered reasonable to look for a linear relation of TOTN and CHL as water quality indicators with the internal and external co-variates SALIN, OXY and wind speed. The trend of TOTN versus SALIN and the wind speed, negative for the former and weakly positive for the latter, can be visually detected in Fig. 2.17.

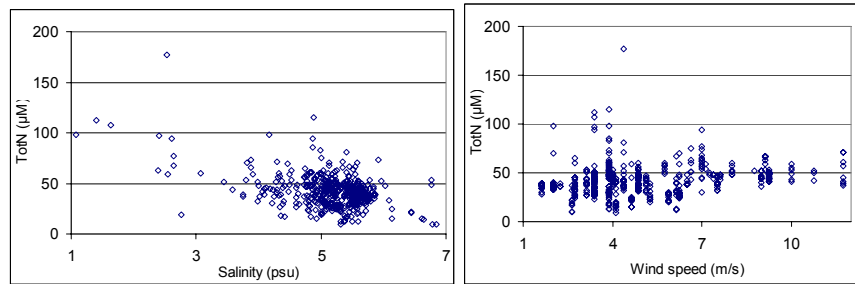


Fig. 2.17: TOTN original data values plotted against salinity (a) and wind speed (b).

Two linear relationships were tested for TOTN:

$$\begin{aligned} \text{TOTN1} &= I_0 + I_{\text{month}} + K_S * \text{SALIN}, & R^2 &= 0.24 \\ \text{TOTN2} &= I_0 + I_{\text{month}} + K_S * \text{SALIN} + K_W * \text{WIND}, & R^2 &= 0.31 \end{aligned}$$

where I_0 is intercept, I_{month} is the monthly deviation value, K_S and K_W are proportionality coefficients for salinity and wind speed..

Table 2.5 Matrix of cross-correlation coefficients (above the main diagonal) and the number of correlated data pairs (below the main diagonal) for the variables under investigation.

	TEMP	SALIN	OXY	PO4P	TOTP	SIO4	NO3N	NO2N	NO23N	NH4N	TOTN	CHL	Wind	Secchi	Depth
TEMP		-7.8E-02	-6.2E-01	-5.1E-01	-1.1E-01	-1.8E-01	-5.0E-01	-4.0E-01	-4.9E-01	1.3E-01	-7.5E-02	-1.6E-01	3.1E-02	-9.5E-02	-1.8E-01
SALIN	2010		-1.8E-01	-1.7E-01	-3.4E-01	-4.8E-01	-4.2E-01	-2.4E-01	-4.1E-01	-1.3E-01	-6.4E-01	-6.3E-01	2.8E-02	1.5E-01	1.8E-01
OXY	1866	1827		2.2E-01	2.9E-01	1.0E-02	3.0E-01	3.1E-01	3.0E-01	-1.9E-01	6.7E-02	7.7E-01	-7.4E-02	-1.2E-01	4.2E-02
PO4P	1793	1824	1847		5.8E-01	5.0E-01	5.0E-01	3.6E-01	5.0E-01	1.6E-01	2.1E-01	-2.8E-01	-4.6E-02	2.9E-01	-1.2E-01
TOTP	1383	1421	1441	1684		3.2E-01	1.9E-01	2.8E-01	1.9E-01	1.9E-01	1.9E-01	7.5E-01	-3.1E-02	7.1E-02	-2.5E-01
SIO4	1631	1659	1695	1821	1497		6.0E-01	1.5E-01	6.1E-01	7.2E-02	4.6E-01	3.4E-01	1.1E-01	1.2E-01	-8.2E-03
NO3N	1682	1694	1726	1908	1534	1719		4.3E-01	1.0E+00	4.0E-02	5.6E-01	6.8E-02	3.9E-02	9.8E-02	2.3E-02
NO2N	1666	1685	1710	1898	1530	1733	1877		4.4E-01	1.3E-01	2.7E-01	1.2E-01	-2.6E-03	-1.6E-02	-6.0E-02
NO23N	1780	1809	1841	2032	1675	1806	1959	1932		4.2E-02	5.5E-01	5.7E-02	4.9E-02	9.6E-02	1.7E-02
NH4N	1685	1711	1749	1934	1566	1694	1800	1778	1914		2.6E-01	-3.3E-01	3.8E-02	2.4E-02	-1.4E-01
TOTN	956	990	1011	1209	1221	1092	1109	1103	1191	1118		6.4E-01	2.0E-01	-1.6E-01	3.6E-02
CHL	58	65	64	69	51	66	54	44	65	64	35		4.7E-01	-2.1E-02	-6.2E-02
Wind	1372	1367	1307	1405	1077	1185	1328	1317	1409	1314	624	96		2.5E-02	8.0E-02
Secchi	872	927	854	899	799	835	847	828	890	831	642	68	413		-8.7E-02
Depth	2068	2078	1954	2080	1679	1813	1932	1921	2051	1951	1190	109	1642	963	

The covariance was estimated by the Regress function in the MATLAB (The MathWorks Inc.). The parameters of the applied relations are shown in Table 2.6 and the original and adjusted annual mean values are shown in Fig. 2.18. The full standard deviation of residuals was reduced from 15.89 μM to 14.23 (10.4% reduction) for TOTN1 and to 13.62 μM (14.3% reduction) in case of TOTN2.

Table 2.6: Parameter values for the relationships TOTN1, TOTN2 CHL1, CHL2 and CHL3

	I_0	K_s	K_O	K_W	R^2	Reduction of St. Dev.
TOTN1	100.84	-11.35			0.24	10.4%
TOTN2	93.06	-11.62		1.84	0.36	14.3%
CHL1	40.03	-6.25			0.34	35.0%
CHL2	46.81	-6.92	0.48		0.35	36.0%
CHL3	47.67	-7.01	-0.43	-0.13	0.35	36.1%

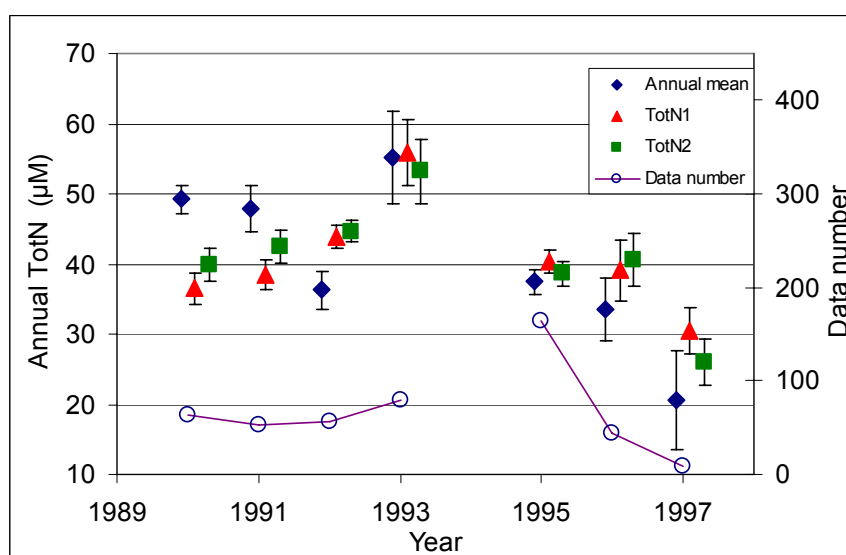


Fig. 2.18: Annual mean TotN concentrations, measured (Annual mean), adjusted for the monthly deviation and for the salinity co-variation (TotN1) as well as for the salinity and wind speed co-variation (TotN2). Bars indicate 95% confidence limits.

The trend of CHL versus SALIN, OXY and the wind speed, negative for the first and positive for the latter two, can be visually detected in Fig. 2.19. Although oxygen concentration does not belong strictly to the external variables of the ecological system, the possible reduction of CHL variability due to the accounting for OXY as a covariate measured within many monitoring programs could considerably reduce the uncertainty of estimation of EQR. A few data for CHL allowed the analysis for only two years, 1990 and 1995 (Fig. 2.20). There were only two data values in years 1991 and 1997.

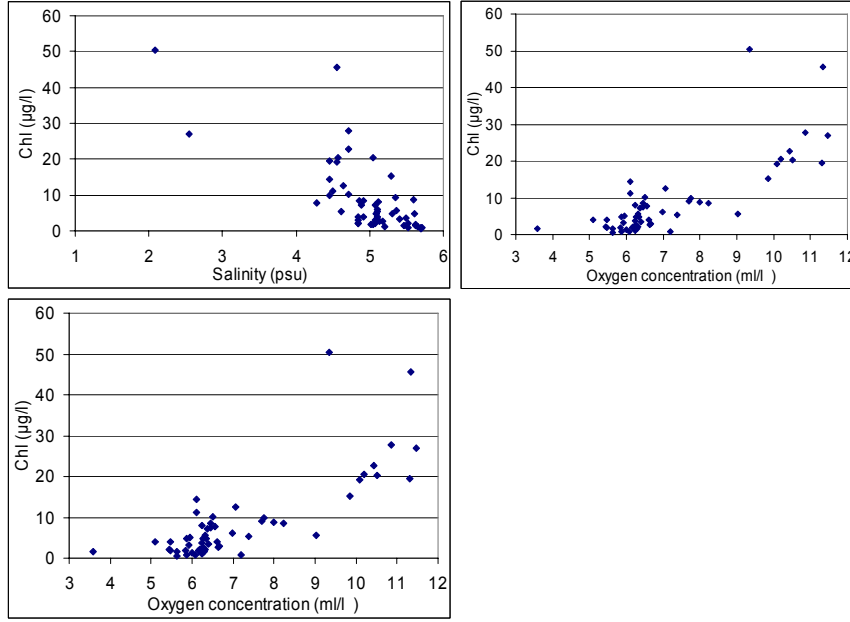


Fig. 2.19: Chl original data values plotted against salinity, oxygen concentration and wind speed.

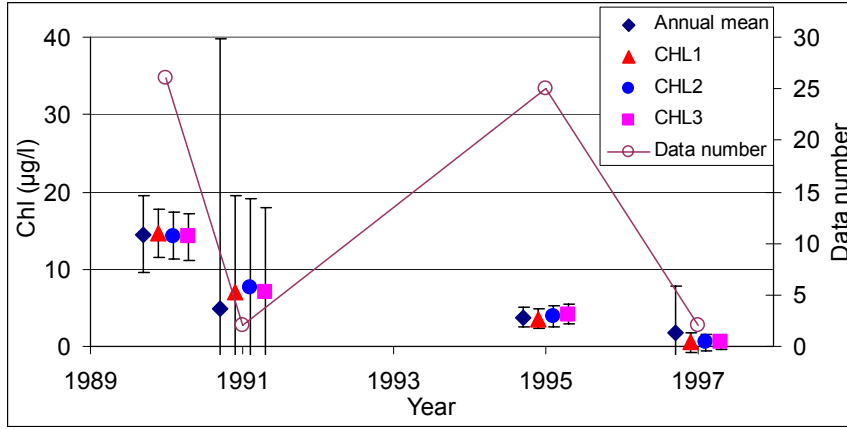


Fig. 2.20: Annual mean CHL concentrations, measured (Annual mean), adjusted for the monthly deviation and for the salinity co-variation (CHL1), for the salinity and oxygen co-variation (CHL2) as well as for the salinity, oxygen and wind speed co-variation (CHL3). Bars indicate 95% confidence limits.

The linear relationships tested were

$$\begin{aligned} \text{CHL1} &= I_0 + I_{\text{month}} + K_S * \text{SALIN}, & R^2 &= 0.34 \\ \text{CHL2} &= I_0 + I_{\text{month}} + K_S * \text{SALIN} + K_O * \text{OXY}, & R^2 &= 0.35 \\ \text{CHL3} &= I_0 + I_{\text{month}} + K_S * \text{SALIN} + K_O * \text{OXY} + K_W * \text{WIND}, & R^2 &= 0.35 \end{aligned}$$

where K_S , K_O and K_W are the regression coefficients for salinity, oxygen and wind speed respectively (Table 2.6). The standard deviation of the residuals was reduced from 8.73 to 5.64 for CHL1 (35%), 5.59 for CHL2 (36%) and 5.58 $\mu\text{g/l}$ for CHL3 (36.1% reduction).

Discussion

The variability of the both selected water quality indicators, TOTN and CHL, is to a large extent (24 and 34% respectively, Table 2.6) statistically explained by the variability of salinity, which could be caused by either the fresh river water inflow, water exchange with the open Baltic Sea (saline water inflow) or vertical salinity stratification in the area. The additional accounting for the wind speed increases the explained part of TOTN variability up to 36%. The similar accounting for the oxygen concentration and wind speed variability nevertheless did not give any substantial increase to the variability of CHL explained by the salinity (the increase from 34% to 35%). The wind effect on the TOTN could be explained by the increase of the upward flux of nitrogen from the deeper layers of the basin. High wind speed and the accompanying larger total nitrogen concentration on the other hand do not necessarily cause the increase of the CHL concentration due to the bottom sediment resuspension and the decrease of the water transparency. Unfortunately the latter guess could not be checked due to the scarce available Secchi depth data in the area.

2.5.5 Latvian coastal areas in the Gulf of Riga example

Introduction

The Latvian coastal areas of the Gulf of Riga are characterized by a highly regular exposed coastline without gulfs, embayments, connected lagoons, or islands (Fig. 2.21). The coast is mainly formed in ancient sea bottoms of older Baltic Sea transgression stages and therefore sandy beaches predominate. On the eastern shore, boulders and stones occur on beaches and sea bottoms where glacial moraine material or dolomite bedrock crop out. In the South, the rivers Lielupe, Daugava and Gauja fall into the Gulf. Their combined freshwater plumes form a nutrient enriched salinity gradient zone, as the Daugava alone accounts for approximately 60% of the riverine nutrient load to the Gulf of Riga (Laznik et al. 1999).

Preparing the implementation of the EU Water Framework Directive in Latvia (DANCEE 2003), it was suggested to treat the salinity gradient zone in the Southern Gulf as a transitional water body (GoRTr), while the rest of the coastline was differentiated according to bottom type into Gulf of Riga sandy coast (GoRSa) and Gulf of Riga stony coast (GoRTr). The sandy coast is predominantly found in the Western Gulf, while coastal areas in the Eastern Gulf belong to the stony coastal type (Fig. 2.21). However, both coastal types are morphologically similar, with a regular coastline and high water exchange with the open part of the Gulf.

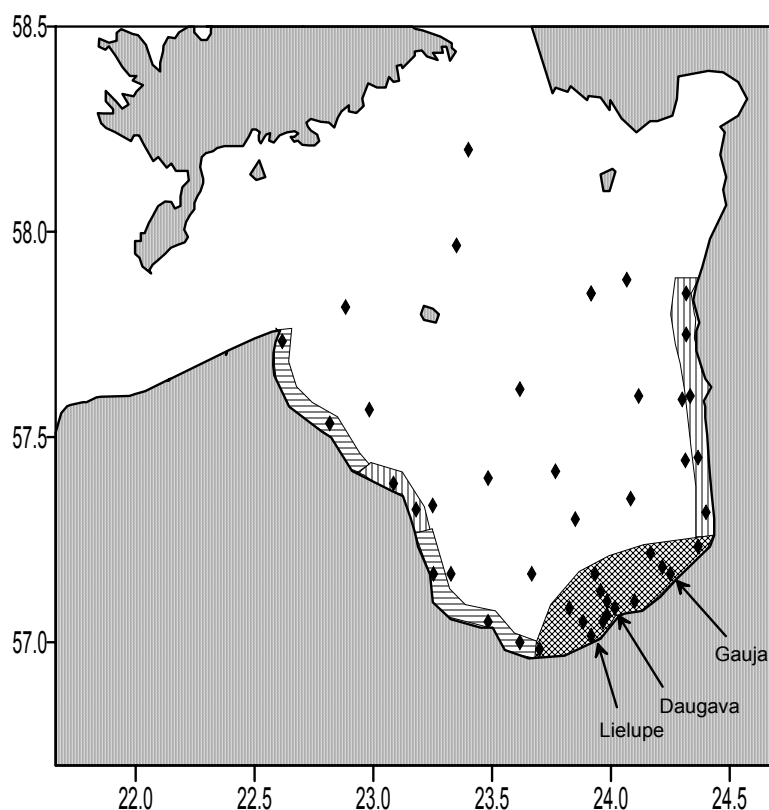


Fig. 2.21: Coastal types in the Gulf of Riga (horizontal – Gulf of Riga sandy coast, vertical – Gulf of Riga stony coast, cross-hatching – Gulf of Riga transitional waters). Monitoring stations are indicated by rhombs, arrows denote major river mouths)

Statistical analysis of water quality elements focused on indicators suggested for assessment under the EU Water Framework Directive in Latvia (DANCEE 2003). These were – among others – winter nutrient concentrations and summer chlorophyll *a*, for which regression models were established to reduce the data variability, using covariates like salinity or meteorological conditions at the time of sampling. General Linear Models (GLM), implemented in STATISTICA software, were used to account for the effect of covariates. All statistical analysis was based on Latvian national marine monitoring data.

Winter nutrient concentrations

Regular ice cover makes monitoring of winter nutrient concentrations in the Gulf of Riga difficult. Winter nutrient concentrations are mostly measured in February, but when February data are lacking, January and sometimes March measurements are used to describe the winter nutrient pool. Therefore, for the statistical analysis “winter” was defined as the period up to the beginning of the spring bloom, i.e. January – March, and data from 1973 – 2004 were used.

Winter nutrient observations for DIP, DIN, total N and total P in the transitional waters linearly decreased with salinity and could be well de-

scribed by conservative mixing between a marine and a freshwater end member. Linear mixing models for each winter monitoring survey were therefore used to adjust winter nutrient observations to a fixed, intermediate salinity (~4.8). Since many observations from the two coastal water bodies also exhibited lowered salinity, they were included into the model and adjusted to reference salinity of 5.5. However, as only few observations from sandy and stony coasts were available, the mixing models mainly describe the winter nutrient conditions in the transitional waters.

Defining the freshwater end member in the mixing relationship, the high variability of nutrient concentrations in the winter runoff was taken into account. The relative standard deviations of the average winter nutrient concentrations in the freshwater load to the Gulf of Riga ranged from 22% for total nitrogen to 34% for DIP (data from 1973 – 2003, January to March). The salinity intercept of the mixing relationship was therefore allowed to vary for each monitoring survey. On the other hand, usually relatively few data points from the gradient zone were available for each given survey, because the size of the river plume area in the Southern Gulf of Riga is highly variable (Stipa et al., 1999, Müller-Karulis, 1999).

To reduce the number of parameters necessary to describe the mixing relationship, the marine end member concentration was not included as a parameter into the mixing model, but its salinity and respective nutrient concentration were calculated for each survey as the average of all observations from water depths ≥ 20 m outside coastal and transitional waters. The Gulf of Riga is relatively shallow (average depth 26 m), and due to the lack of a permanent halocline, completely mixed in winter. At high freshwater runoff the river plume forms a shallow surface layer that occasionally spreads beyond the area technically defined as transitional waters. Therefore, to avoid including observations affected by the freshwater plume, calculation of the marine end member properties was restricted to the bottom water.

The model constraint of a predetermined marine end member was implemented into a GLM by transforming the data to achieve a model without intercept, where $K_{s,survey}$, the slope with respect to salinity, was allowed to vary between monitoring surveys. Thus, the following model was used to describe nutrient dynamics at each surface layer (< 20 m) sampling horizon for all monitoring surveys:

$$\text{Nutrient Concentration} - \text{Marine end member nutrient concentration} = K_{s,survey} * (\text{Salinity} - \text{Marine end member salinity})$$

The mixing model was highly significant to describe the concentrations for DIN, DIP, total nitrogen and phosphorus at most winter monitoring surveys ($p \leq 0.05$ for all models, see Table 2.7 and Appendix Table B.1). All surveys with data available for transitional/coastal areas and data for the determination of the marine end member were included into the mod-

els. Winter DIP and total phosphorus data cover a longer time series, therefore the number of surveys included into the model was larger than for DIN or total nitrogen. Most insignificant slopes resulted from surveys that had no observations at low salinities (< 4.3).

Table 2.7: Winter nutrient concentration model properties

Parameter	surveys included	significant slopes ($p \leq 0.05$)	proportion of significant slopes	R ² adjusted
DIP	50	36	72%	0.72
P _{tot}	50	30	60%	0.67
DIN	42	36	86%	0.93
N _{tot}	33	30	91%	0.93

Nutrient concentrations were then adjusted to reference salinities (4.8 for transitional waters, 5.5 for sandy and stony coast) using the slope determined for the respective nutrient and monitoring survey. This greatly reduced the variance of the winter observations in the transitional waters (Table 2.8, Fig. 2.22), where the standard deviation of the observations was reduced by 60.3 – 81.1%. The procedure also removed bias in determining average concentrations for the transitional area and greatly decreased the interannual variability.

Large reductions of the survey averages were achieved when the survey covered regions of low salinity (1 – 2) and corresponding high nutrient concentrations, for example in surveys 27 and 28 for DIN. The opposite case, when the adjustment procedure increased the survey average, occurred only rarely, most pronounced for DIP in cruise 6, where observations at high salinity (~ 6), were adjusted to the lower reference salinity. For sandy and stony coast, the model could only be applied to 2 – 3 surveys because many coastal surveys lacked marine end member data. Because salinities at sandy and stony coast were often close to the marine endmember salinity, the adjustment did not always reduce the data variance. However, the model performed slightly better at the Gulf of Riga sandy coast, which is located more closely to the river mouths than most data points from the Gulf of Riga stony coast.

Table 2.8: Average standard error of winter survey nutrient data and adjusted values and their relative change due to the adjustment procedure

		GoRSa	GoRSt	GoRTr
DIP	raw	0.140	0.063	0.192
	adjusted	0.121	0.073	0.076
	rel. change	- 13.3%	+ 16.5%	- 60.3%
P _{tot}	raw	0.137	0.124	0.183
	adjusted	0.145	0.155	0.093
	rel. change	+ 6.47%	+ 25.3%	- 49.2%
DIN	raw	0.158	0.290	0.568
	adjusted	0.127	0.318	0.153
	rel. change	- 19.9	+ 10.0	- 73.0%
N _{tot}	raw	0.086	0.146	0.364
	adjusted	0.073	0.121	0.069
	rel. change	- 15.6%	- 17.1%	- 81.1%

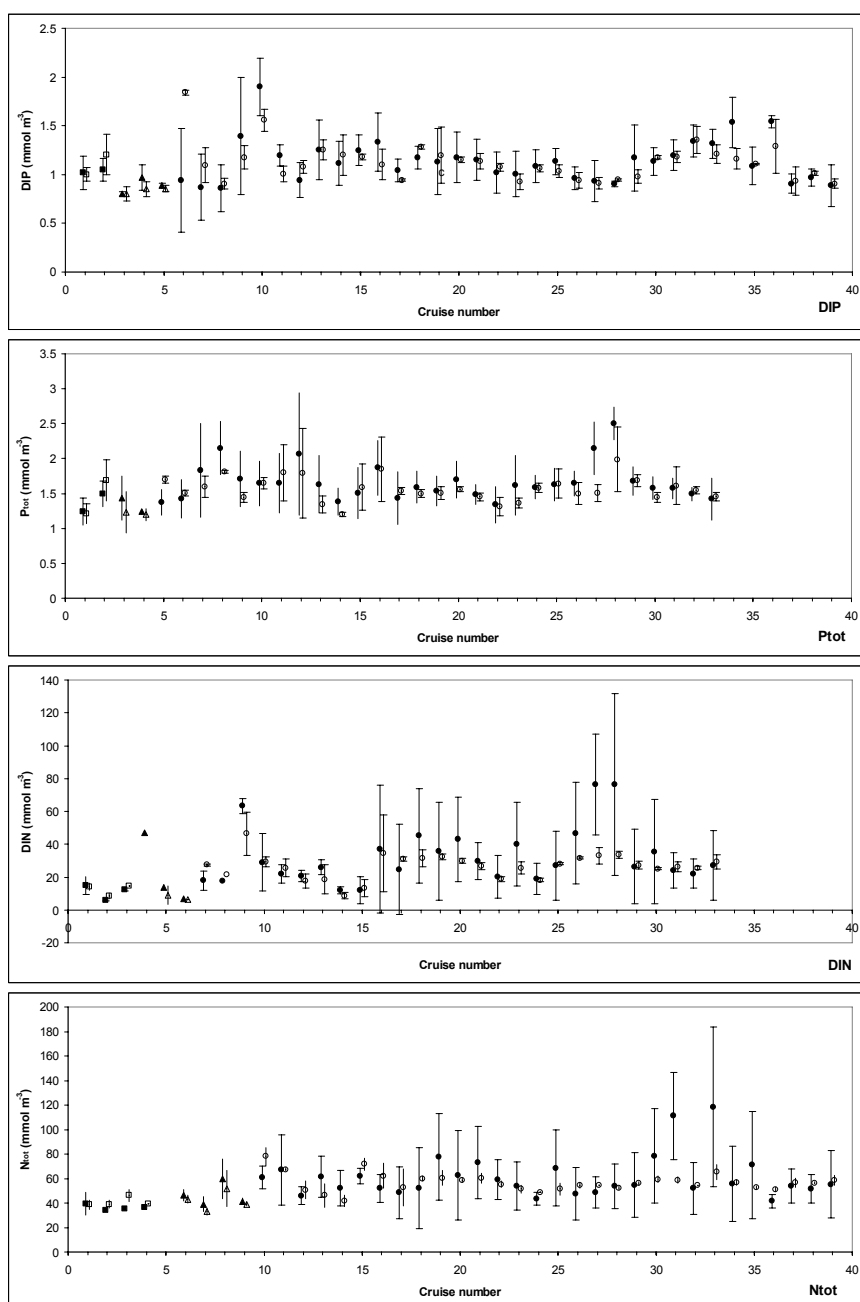


Fig. 2.22 Winter nutrient data adjustment to reference salinities (filled symbols: raw data, open symbols: adjusted, squares, triangles and circles denote Gulf of Riga sandy coast, Gulf of Riga stony coast, and Gulf of Riga transitional waters, respectively). The error bars show the standard error of the means.

Even though adjustment to reference salinity greatly reduced the data variability, classification of winter nutrient concentrations in transitional waters was not straightforward. First, since conservative mixing of freshwater and a marine end member dominated winter nutrient dynamics, their concentrations and therefore also quality classification largely depends on the respective end member values.

Based on the draft of the EU Marine Strategy, it is quite clear that a definition of good environmental quality will also be established for open marine waters. Given conservative mixing, the quality class delimitations for the transitional waters could then be defined at reference salinity by interpolating between the respective freshwater and marine values. However, when freshwater and marine end members belong to different quality classes, the final classification of the transitional waters would then depend on the choice of reference salinity (Fig. 2.23). Depending on the choice of reference salinity, the data in this example would be assigned to different quality classes after salinity adjustment.

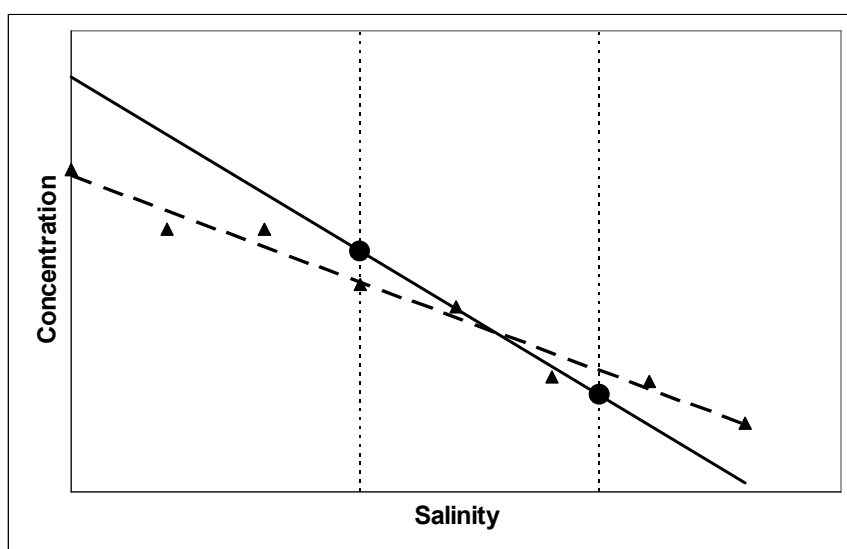


Fig. 2.23 Classification of transitional water winter nutrient concentrations, using interpolation (solid line) between riverine and marine class boundaries to establish a quality criterion. Boundary concentrations corresponding to two different reference salinities (stippled lines) are shown as filled circles. Triangles represent data from a hypothetical survey and their mixing line (broken line).

Summer chlorophyll *a*

In the Gulf of Riga, autumn mixing - the end of the summer season - occasionally occurs already in September. Therefore, contrary to the HELCOM COMBINE guidelines, the summer months were defined as the period June - August. Only data collected between 1996 and 2003 were considered in the statistical analysis, because prior to 1996 sampling mainly took place in August and June/July data are only sparsely available.

Chlorophyll *a* samples were collected with an integrated sampler from water depths 0 - 10 m. Potential water sample covariates were averaged from measurements at 1, 5, and 10 m depth. Meteorological data (wind speed, air temperature) were measured concurrently. Chlorophyll *a* data were log-transformed to achieve normal distribution, while for other parameters transformation was not necessary.

Several linear regression models were tested to describe the variance of summer chlorophyll *a* in the three water bodies of the Gulf of Riga. The best fit was achieved by a model including yearly (I_{year}) and monthly (I_{month}) differences between chlorophyll *a* levels, dependency on wind-speed ($I_{\text{windclass}}$), and a linear relation with air temperature (K_t) and salinity (K_s). Model coefficients are listed in Appendix Table B.2.

$$\ln[\text{CHL}] = I_0 + I_{\text{year}} + I_{\text{month}} + I_{\text{windclass}} + K_t * \text{AirTemp} + K_s * \text{Salinity}, \\ R^2_{\text{adj}} = 0.66$$

I_{month} showed that June chlorophyll *a* concentrations were significantly larger than in July or August. Chlorophyll *a* concentrations also tended to decrease with increasing salinity and were negatively correlated with air temperature. Low air temperatures mainly occurred in June, when chlorophyll *a* concentrations were highest. To characterize the effect of wind-speed on summer chlorophyll *a*, models including three windspeed classes ($\leq 2.5 \text{ m s}^{-1}$, $> 2.5 \text{ m s}^{-1}$ and $\leq 5 \text{ m s}^{-1}$, $> 5 \text{ m s}^{-1}$) performed better than models assuming linear dependence on wind speed. $I_{\text{windclass}}$ was smallest for the intermediate wind class. This indicates that both low and high wind speeds are beneficiary for phytoplankton growth. Calm conditions are known to promote the growth of cyanobacteria (Kanoshina et al. 2003, Wasmund 1997), while high wind conditions cause mixing and nutrient transport through the thermocline, triggering the growth of non-nitrogen fixing algae.

Summer chlorophyll *a* data were adjusted to August as the most important sampling month, salinity of 5.0 for sandy/stony coast and 4.6 for transitional waters, air temperature of 18°C and intermediate windspeed ($> 2.5 \text{ m s}^{-1}$ and $\leq 5 \text{ m s}^{-1}$). From the adjusted data annual summer averages were calculated and compared to the raw data averages (Table 2.9, Fig. 2.24). Adjustments reduced the residual standard error by 2.4% and 5% for sandy coast and transitional waters, but increased the standard error by 8.5% for Gulf of Riga stony coast. In almost all cases the model reduced the summer chlorophyll *a* average, primarily because the data was adjusted for the systematically larger chlorophyll *a* values measured in June. However, failure to reduce the data variability for the Gulf of Riga stony coast suggests that type-specific model parameters should be used, after sufficient data has been collected by regular monitoring.

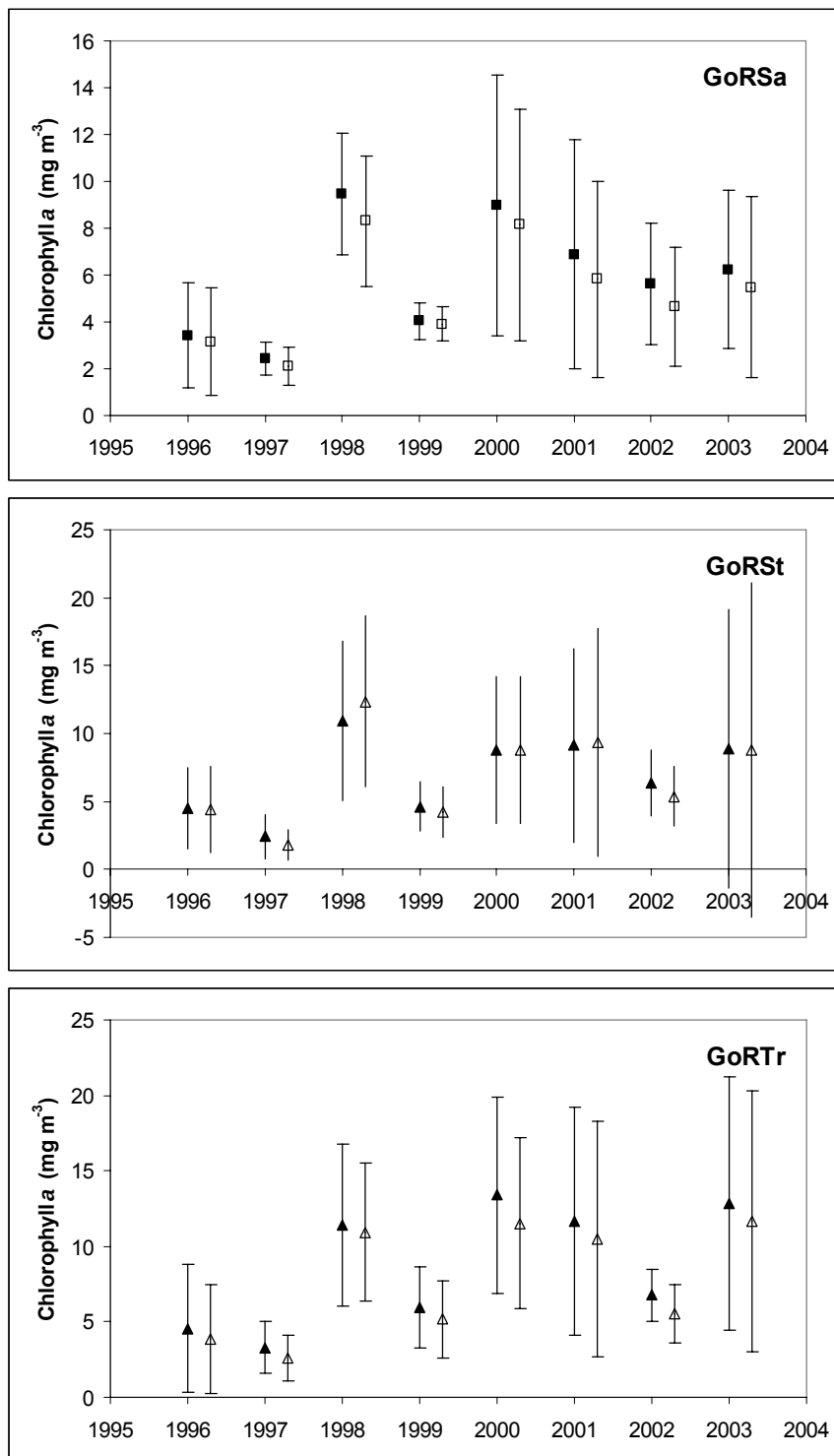


Fig. 2.24: Raw (filled symbols) and adjusted (open symbols) summer average chlorophyll *a* concentrations for Gulf of Riga sandy coast (top), stony coast (middle) and transitional waters (bottom). The error bars show the standard error of the means.

Table 2.9: Average standard error of summer chlorophyll *a* raw data and adjusted values for 1996 – 2003 and its relative change due to the adjustment procedure.

		GoRSa	GoRSt	GoRTr
Summer chlorophyll <i>a</i>	raw	2.84	4.68	4.77
	adjusted	2.77	5.08	4.53
	rel. change	- 2.4%	+ 8.5%	- 5.0%

Discussion

The two examples – adjustment of winter nutrient concentrations and summer chlorophyll *a* for their covariates – characterize two extremes, where the data variability is greatly reduced (winter nutrients in transitional waters) or where only small adjustments can be made (summer chlorophyll *a*). In the first case, the large portion of the variance covered by the salinity covariate indicates, that the winter nutrient concentrations in the transitional zone depend so strongly on the riverine and marine concentrations, that an independent water quality classification based on this indicator might not be useful. Monitoring of winter nutrient concentrations in transitional waters in this case rather serves the purpose of surveillance monitoring of point source discharges or extreme events.

On the other hand correction for covariates reduced the variance of summer chlorophyll *a* data only by 5% in the transitional waters. The adjustment also did not remove the high interannual variability of the data (Fig. 2.24). In this case, water quality classification should not be based on data from a single year, but instead on observations from several years to stabilize the indicator variability.

2.5.6 Curonian Lagoon example

Introduction

The Curonian Lagoon (Fig. 2.25) is a large (1584 km²) shallow transitory freshwater body situated in the south-eastern Baltic Sea and separated from the sea by the Curonian Spit (Gailiusis et al. 2005). The narrow (0.4-1.1 km) Klaipeda strait (port area) connects the Lagoon with the sea (Olenin & Daunys 2004).

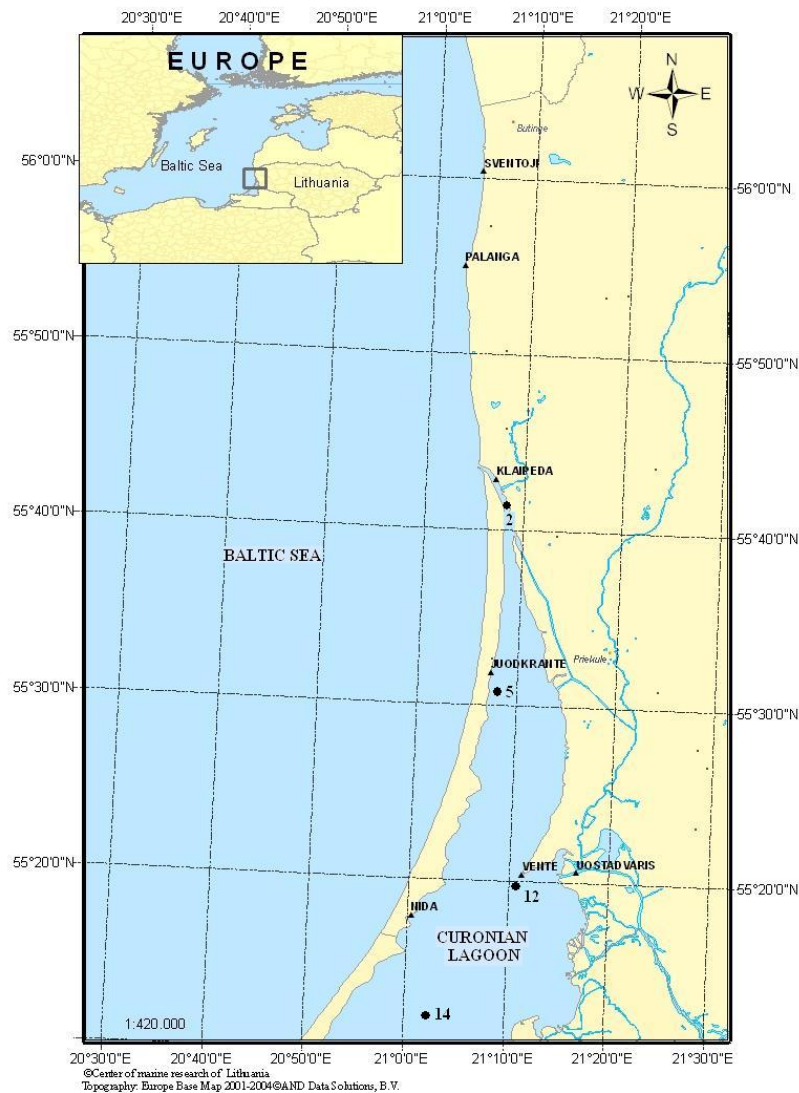


Fig. 2.25: Locations of sampling stations in the Curonian Lagoon used in the analysis

In the Curonian Lagoon the river Nemunas contributes with 92% of the total fresh water yield. The average residence time for fresh water is estimated to be 3.3 months for the Lagoon (Chubarenko et al. 2002). The Klaipeda Strait and the northern part of the Lagoon are influenced by seawater intrusions from the Baltic Sea. The water exchange through the Klaipeda Strait averaged over many years gives an annual outflow of 27.811 km^3 and inflow of 5.546 km^3 .

During the year the seawater flow is observed on average 40 times and lasts about 70 days (Gailiusis et al. 2005). One to two days seawater inflows are most frequent with a residence time of mixed waters within the Lagoon not longer than 5 days. The seawater intrusions are mostly restricted to the northern part of the Lagoon, only rarely propagating ca. 40 km into its central part (Olenin & Daunys 2004). The rapid and irregular

water exchanges cause large fluctuations in temperature, salinity and other characteristics (Gailiusis et al. 2005).

The average depth of the Lagoon is approx. 3.8 metres. The strait is ca. 11 km long, with artificially deepened water ways to 14 metres depth. The eastern side of the study area (mainland shore) represents a shallow plain gently sloping westward down to 1-2 metres depth, whereas its western side (the Curonian Spit shore) is deeper, on some sites reaching 4 metres depth (Olenin & Daunys 2004). The main bottom sediments in the Lagoon are sand and silt, on sites with shell deposits. The northern part of the Lagoon is a transitory area of sediment transportation, while the central part is most heterogeneous with respect to bottom geomorphology and sediment type. Here the prevailing type is fine sand, on sites mixed with gravel and pebbles, peat and moraine. Muddy bottoms prevail in local depressions in the deeper western part of the Lagoon along the Curonian Spit (Olenin & Daunys 2004). The bathymetric structure of the Curonian Lagoon forms ideal conditions for the occurrence of wind-wave resuspension (Chubarenko et al. 2002).

The most important ecological problem in the Curonian Lagoon is the ongoing eutrophication, which is caused by nutrient and organic substances entering the Lagoon with the water from the Nemunas and other rivers, carrying wastewater from cities and settlements. The hydrological features of the Curonian Lagoon – shallowness, limited water exchange with the Baltic Sea and strong inertia of natural processes stimulates the eutrophication process and aggravates its consequences for the ecosystem. The intensity of phytoplankton development essentially determines the water quality and productivity of a water body.

The aim of this analysis was to identify the main physical forcing variables (e.g. salinity, wind speed), which induce residual variation in water quality indicators. Total phosphorus, total nitrogen, secchi depth and chlorophyll a were used as indicators for the analysis. The data used in this analysis is taken from the National monitoring programme and spans the years 1992-2003. Data from four monitoring stations were used, two of them (2 ST, 5 ST) represent the northern part, the other two (12 ST, 14 ST) – the central part of the Curonian Lagoon (Fig 2.25).

Methods

The objective of the analysis was to test different linear models to find significant relationships between indicators and physical forcing variables individually and in combination (Table 2.10). The models were run using General Linear Models (GLM) procedure in the STATSOFT STATISTICA 6.0.

Results and discussion

Total Nitrogen (TN)

During the 1992-2003 period annual mean TN concentrations in the northern Lagoon was $1447 \mu\text{g l}^{-1}$, and in the in central part – $1575 \mu\text{g l}^{-1}$, although the concentrations ranged from 577 to $3000 \mu\text{g l}^{-1}$. Much of the variability is caused by seasonal variation of TN. Elevated concentrations of TN are observed in winter season and early spring when TN exists in mineral form after intensive mineralization of organic matters and is not utilized by plankton and other vegetation, as biological processes are not going on or occur at very low intensity. In the end of the vegetation season (late summer, autumn) when biological processes are stopping and mineralization starts, the TN concentration in the water increases.

Table 2.10: Water quality indicators, physical forcing variables in the analysis.

Indicators	Year period	Sampling frequency
Total Nitrogen, [TN]	1992, 1997-2003	monthly
Total Phosphorus, [TP]	1992-2003	monthly
Secchi Depth, [SD]	1992-2003	monthly
Chlorophyll-a, [CHL]	1992-2003	Since 1997 monthly
Physical Forcing variables		
Salinity [SAL]	1992-2003	monthly
Water temperature [TEMP]	1992-2003	monthly
Wind velocity [WI V]	1992-2003	monthly
Current velocity [CU V]	1992-2003	monthly
Wave height [WA H]	1992-2003	monthly

The lowest concentrations of TN are observed during late spring and the beginning of the summer (May-July) as mineral nitrogen is consumed by phytoplankton and other vegetation and is transformed to organic form (70-90% of total nitrogen).

Beside the seasonal variability of TN concentration, the influence of other factors on indicator was analysed. Most correlated factors were included in the linear models. In the northern part of the Curonian Lagoon, which is influenced by seawater, there was a negative relationship between TN and salinity (Fig. 2.26). The strongest and most statistically significant correlations between these two variables was determined in summer ($r=-0.48$) and winter ($r=-0.47$), lower correlation was found in autumn ($r=-0.33$). In spring when river run-off usually dominates, salinity influence is lowest, and there is no relationship during this season. The influence of other factors was low or not significant. Consequently the model for the northern part took into account the salinity relationship and seasonal pattern (Table 2.11).

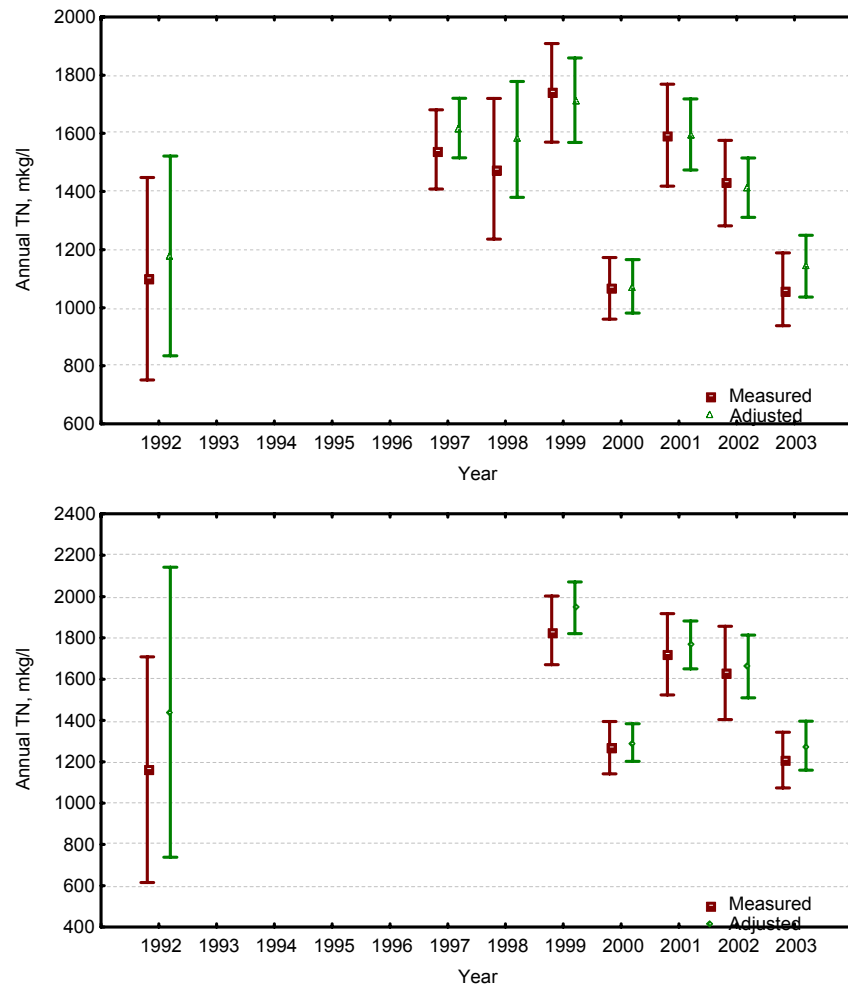


Fig. 2.26: The annual mean TN, measured and corrected in the northern part (top) and central part (bottom) of the Curonian Lagoon in 1992, 1997-2003. For the northern Lagoon TN concentrations adjusted to salinity (average: 1.53 psu) co-variation and seasonal variation, for the central Lagoon – to seasonal variation. The error bars show the 95% confidence of the means.

Results of the model are shown in Fig. 2.26 where original and salinity-season adjusted annual means of TN are presented. The adjusted mean values deviated between -7.55% to 16.46% from the original means. Standard error of the mean was reduced from $39.79 \mu\text{g/l}$ to $33.20 \mu\text{g/l}$ (17% reduction).

For the central part of the Lagoon the model included only seasonal adjustment since no relationships were determined with other physical factors (Table 2.11). The adjusted mean values deviated between -13.55% to 11.29% of the original means. Standard error of the mean was reduced from $49.64 \mu\text{g/l}$ to $40.89 \mu\text{g/l}$ (18% reduction).

Table 2.11: Models for indicators for northern and central part of the Curonian Lagoon (NL=Northern part of the Lagoon, CL=Central part of the Lagoon). Parameter estimates are found in Appendix Table C.1-8.

Indicator	Part of the Lagoon	Model	R ²	Reduction of St.Error
TN	NL	TN = Intercept + Residual _{obs} + Ks*Salinity	-0.26	17%
	CL	TN = Intercept + Residual _{obs}	0.25	18%
TP	NL	TP = Intercept + Residual _{obs} - Ks*Salinity	0.20	10%
	CL	TP = Intercept + Residual _{obs}	0.20	11%
SD	NL	SD = Intercept + Residual _{obs} + Ks*Salinity	0.31	19%
	CL	SD = Intercept + Residual _{obs} - Kw*wind velocity	0.12	5%
CHL	NL	CHL = Intercept + Residual _{obs}	0.012	3%
	CL	CHL = Intercept + Residual _{obs} - Kw*wind velocity	0.17	12%

Total Phosphorus (TP)

There was a statistically significant difference ($p=0.001$) between the means in northern and central parts of the Lagoon. During the 1992-2003 period the mean TP concentrations in the northern part were $84 \mu\text{g l}^{-1}$ and $134 \mu\text{g l}^{-1}$ in the central part. The dynamics of TP concentrations has a seasonal pattern in the Lagoon, which determines the annual variability of TP concentrations. Seasonal water run-off unevenness, biological processes and other factors determine the seasonal changes of TP concentrations (Zaromskis 1996). The highest concentrations were characteristically found in the end of vegetation season (August-September) when large amounts of dead plankton and organic substances start to mineralize intensively. Higher concentrations were determined in the winter period as biological process rates are low.

From the physical factors in the northern part of the Lagoon only salinity correlated with TP. In comparison with the Curonian Lagoon seawater is 3-5 times less rich with biogenic matter therefore seawater inflow in the northern part of the Lagoon results in decreasing TP concentrations. The highest correlation with salinity was found in summer ($r=-0.47$) and autumn ($r=-0.41$).

Results from the model for the northern Lagoon are shown in Fig. 2.27, where original and salinity-season adjusted annual means of TP are presented. The adjusted mean values deviated between -10.35% to 27.68% from the original means. Standard error of the mean was reduced from $2.91 \mu\text{g l}^{-1}$ to $2.56 \mu\text{g l}^{-1}$ (10% reduction).

For the central part of the Lagoon the model included only seasonal adjustment (Table 2.11) as no relationships were determined with other physical factors. The adjusted mean values deviated between -16.69% to 0% from the original means. Standard error of the mean was reduced from $4.8 \mu\text{g l}^{-1}$ to $4.3 \mu\text{g l}^{-1}$ (11% reduction).

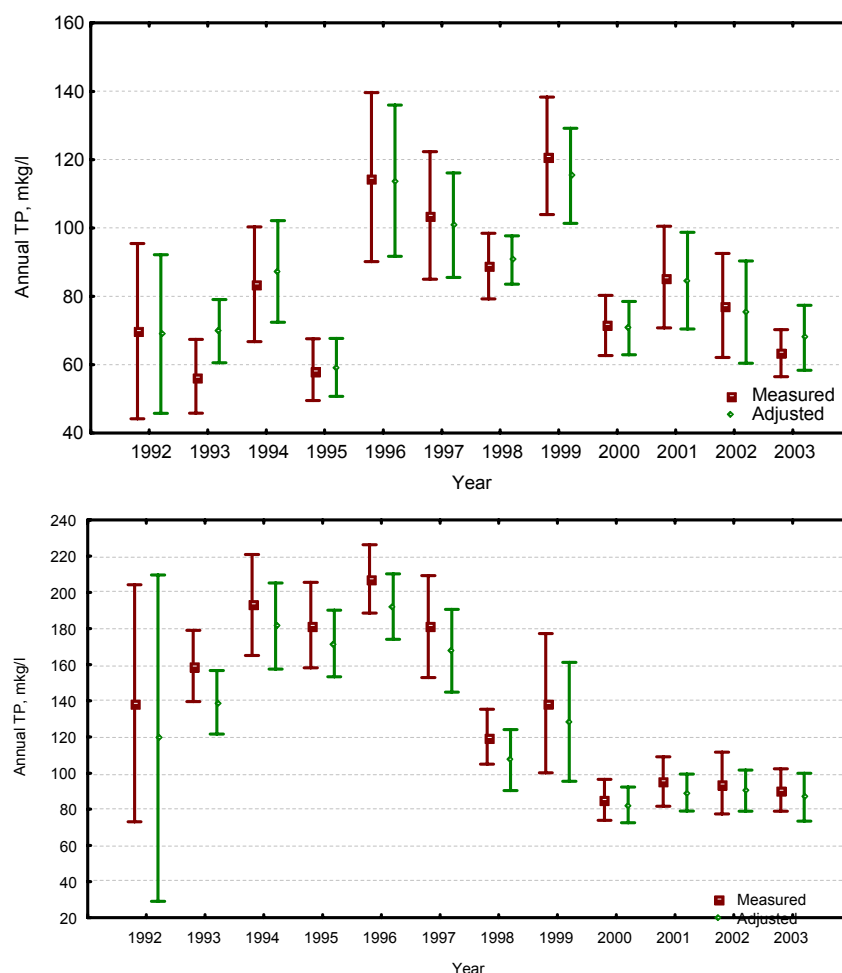


Fig. 2.27: The annual mean TP, measured and corrected in the northern part (top) and central part (bottom) of the Curonian Lagoon in 1992-2003. For the northern Lagoon TP concentrations are adjusted to salinity (average: 1.69 psu) co-variation and seasonal variation and for the central Lagoon – to seasonal variation. The error bars show the 95% confidence limits for the means.

Secchi Depth (SD)

SD variability is driven by fluctuations of dispersed heterogenic particles in the water column, mechanical and organic particles from rivers and plankton abundance. SD can be reduced by resuspension of particles from sediments forced by hydrodynamic processes or technogenic impact. Mean SD in the northern part of the Curonian Lagoon was 0.9 m (in the Strait area -1.1 m), in the central part – 0.8 m, although SD in the Lagoon ranged from 0.2 m to 3.8 m.

Changes in SD variation are observed during different seasons. Because of scarcity of winter data, it is not clear what transparency is characteristic to the winter season. Higher SD in the northern Lagoon was determined in autumn (October-November). In the central part of the Lagoon higher transparency in water was found in November-December and spring (April).

Two different models were developed for analyzing the northern and central parts of the Lagoon. For the northern part of CL salinity and seasonal adjustment were included into model (Table 2.11).

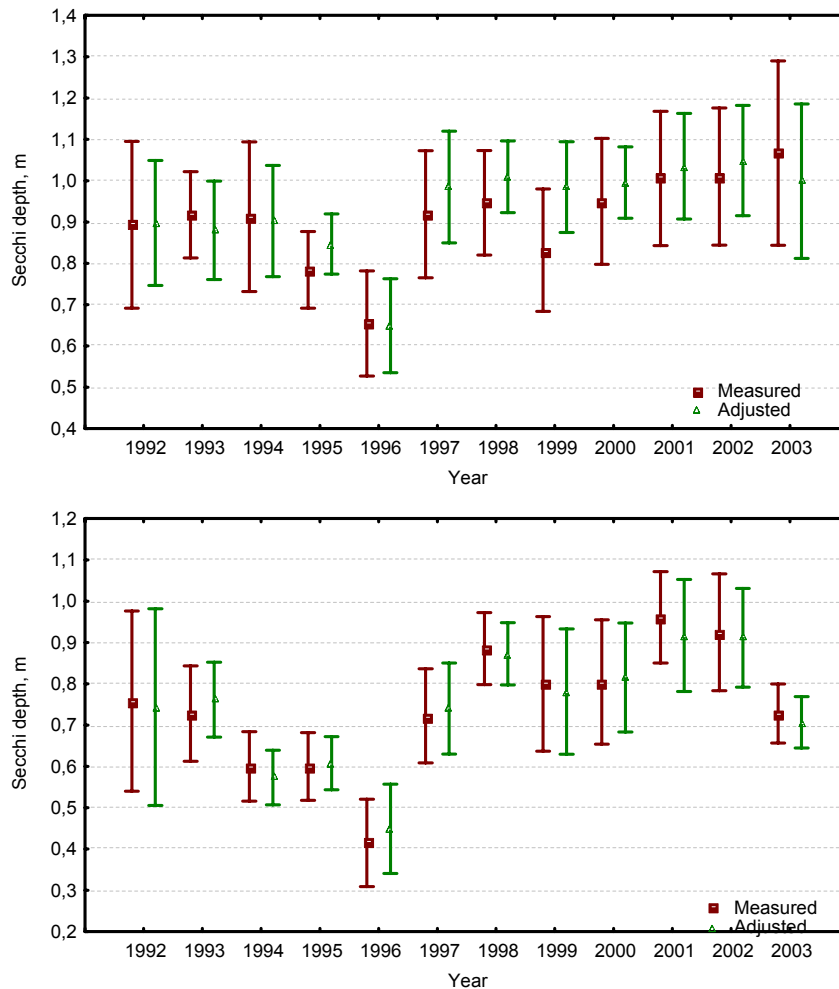


Fig. 2.28: The annual mean SD, measured and corrected in the northern part (top) and central part (bottom) of the Curonian Lagoon in 1992-2003. For the northern Lagoon SD concentrations are adjusted to salinity (average: 1.76psu) co-variation and seasonal variation, for the central Lagoon – to wind velocity (average: 4.63) co-variation and seasonal variation. The error bars show the 95% confidence limits for the means.

The model shows positive impact of salinity as this part of the Lagoon is influenced by more transparent seawater. The highest statistically significant correlation between SD and salinity was determined in summer ($r=0.77$), when the river runoff decreased and better conditions for seawater intrusions are formed. Lower correlation with SD was in autumn ($r=0.44$). Because of scarce SD data it is not possible to evaluate the relationship between these variables in winter. Seawater intrusions into CL are less pronounced during the spring as river run-off dominates.

Results of the model for the northern Lagoon are shown in Fig. 2.28 (left column) where original and salinity-season adjusted annual means of

SD are presented. The adjusted mean values deviated between -8.21% to 29.72% from the original means. The standard error of the mean was reduced from 0.26 m to 0.21 m (19% reduction).

For the central part of the Lagoon, which is less influenced by seawater, and is more open to wind impact, another model was used. Wind velocity was included into the model although the correlation with this variable is very low. Seasonal analysis showed that in spring the correlation is highest ($r=-0.52$). The adjusted mean values deviated between -6.05% to 9.51% from the original means. The standard error of the mean was reduced from 0.21 m to 0.20 m (5% reduction).

Chlorophyll-a (CHL)

Chlorophyll-a is a state parameter often used as a measure (indicator) of phytoplankton biomass. Mean annual chlorophyll-a concentration in the both parts of the Lagoon was $48.4 \mu\text{g l}^{-1}$. High standard deviation of chlorophyll-a is caused by strong seasonal variation. The highest concentrations of chlorophyll-a are found in summer-late autumn (July-October) and the lowest in winter.

The analysis of influence of physical forcing variables on chlorophyll-a variability found no significant correlations in the northern part of the Lagoon. Therefore the model for the northern part of the Lagoon included only seasonal adjustment (Table 2.11). The adjusted mean values deviated between -141.94% to 0% of the original means. The standard error of the mean was reduced from $8.05 \mu\text{g l}^{-1}$ to $7.79 \mu\text{g l}^{-1}$ (3% reduction).

Wind velocity was the only variable showing a relationship (although very weak) with chlorophyll-a in the central part of the Lagoon. Seasonal analysis also presented a very low, and statistically not significant, relationship between these two parameters. Consequently the model for the central part took into account the wind velocity relationship and seasonal pattern (Table 2.11). Results of the model are shown in Fig. 2.29, where original and wind velocity-season adjusted annual means of CHL are presented. The adjusted mean values deviated between -152.61% to 201.09% from the original means. The standard error of the mean was reduced from $7.04 \mu\text{g l}^{-1}$ to $6.21 \mu\text{g l}^{-1}$ (12% reduction).

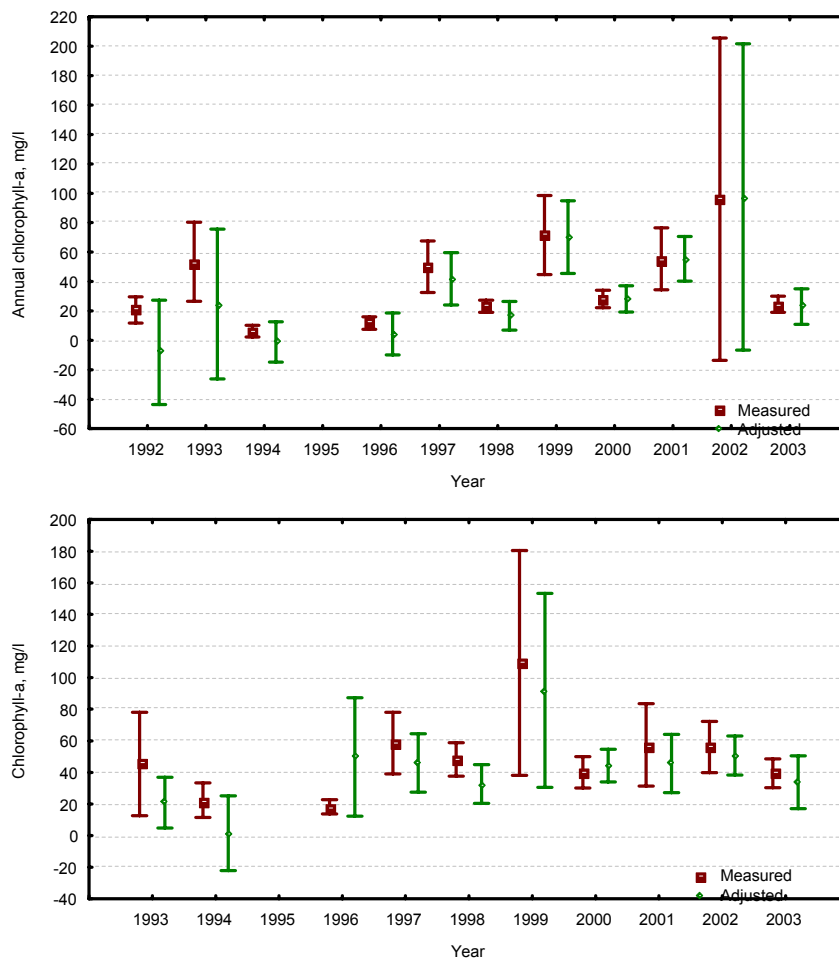


Fig. 2.29: The annual mean chlorophyll-a, measured and corrected in the northern part (top) and central part (bottom) of the Curonian Lagoon in 1992-2003. For the northern Lagoon chlorophyll-a concentrations are adjusted to seasonal variation, for the central Lagoon – to wind velocity (average: 4.74) co-variation and seasonal variation. The error bars show the 95% confidence of the means.

Conclusions

The high annual variability of TN and TP concentrations is greatly determined by the seasonal variation of these indicators. Elevated concentrations are characteristic in the end of the vegetation season (late summer, autumn) and winter and the lowest values are found in late spring and the beginning of summer.

In the northern part of the Lagoon salinity is the main physical forcing variable, correlating negatively with TP and TN and positively with SD. The highest and statistically most significant correlation between these indicators and salinity was found in summer and autumn.

No correlations were found between physical forcing variables and TP and TN in the central part of the Lagoon. From the list of physical forcing variables SD slightly correlated with wind velocity in the central part.

Because of the lack of SD monitoring data, especially in the winter season, SD could not be evaluated for winter and there is no clear seasonal variability of SD.

No correlations were found between chlorophyll-a and physical forcing variables in the northern lagoon. Only a very weak relationship was found with wind velocity in the central Lagoon. Chlorophyll-a annual mean variability was therefore determined by seasonal variation. Highest concentrations are observed in summer-late autumn, lowest in winter.

2.5.7 Limfjorden example

Introduction

Limfjorden is a large estuary in the Northern part of the Jutland peninsula. It is characteristically shallow with a mean depth of 4.3m. The estuary has two mouths, one on the North Sea coast and one on the Kattegat coast. The saline end member is primarily North Sea water, however, there can also be inflows from the Kattegat. Annual freshwater runoff varies between 1800 and 3600 $10^6 \text{ m}^3 \text{ yr}^{-1}$.

The aim of this analysis was to identify possible water quality indicators (for example annual average Secchi Depth) and attempt to reduce the variability in these indicators by taking into account variability in physical forcing variables (e.g. wind speed or water mass mixing-Salinity) and in some cases internal variables (e.g. dependency of Secchi Depth on Chlorophyll concentrations). The data used in this analysis is taken from the National monitoring program and spans the years 1984-2003. Data from seven monitoring stations were used (Fig. 2.30).

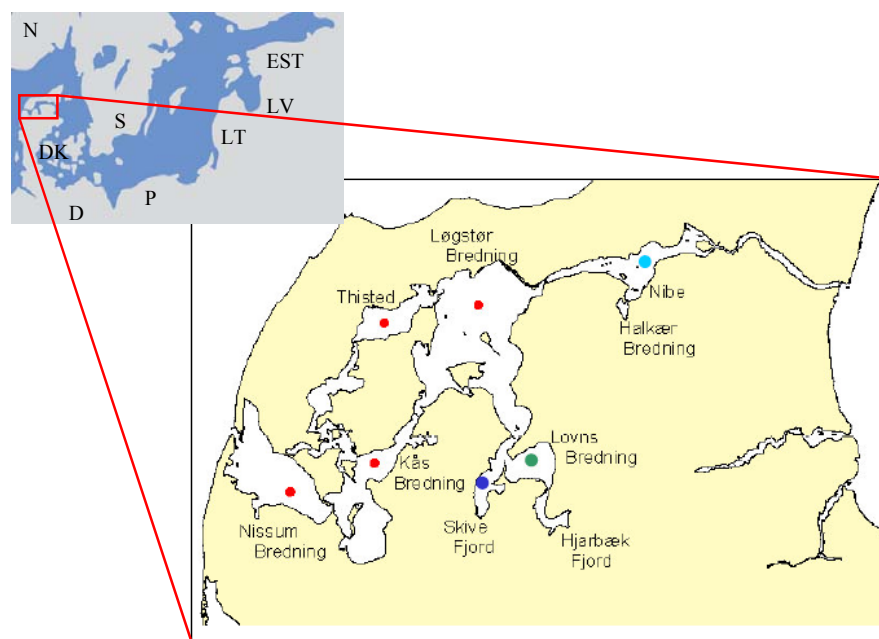


Fig. 2.30: Location of Limfjorden and the sampling stations used in the analysis.

Methods

The schematic in Fig. 2.31 indicates the possible correlation's between indicators and physical forcing variables (Table 2.12) in Limfjorden and was used to select and subsequently test variables. In the modelling relationships between external forcing variables (e.g. radiance, wind, temperature, salinity) and ecosystem variables were examined.

A series of linear models were tested to find significant relationships between indicators and physical forcing variables individually and in combination. The models were run using the General Linear Models (GLM) procedure in the SAS software package (SAS Institute Inc.). The general models were for example

$$\text{Indicator} = \text{Intercept} + K_1 * \text{Var}_1$$

in their most simple form and

$$\text{Indicator} = \text{Intercept} + I_x + K_1 * \text{Var}_1 + K_2 * \text{Var}_2 + K_3 * \text{Var}_3$$

in a more complex situation. I_x represents an intercept parameter that is allowed to vary by class variable x (e.g. month).

External and internal interactions

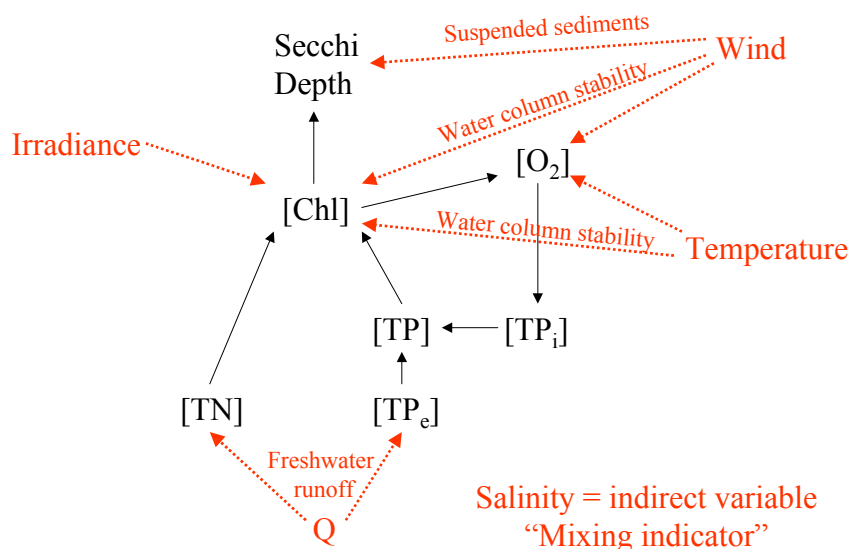


Fig. 2.31: Schematic of possible inter-relations between indicators and physical forcing variables in Limfjorden.

Table 2.12: Indicators and external forcing variables used in the analysis.

Indicators	
Secchi Depth, SD	Annual average
Chlorophyll a concentration, [CHL]	Annual average
Total Nitrogen concentration, [TN]	Annual average
Total Phosphorus, [TP]	Annual average
Physical Forcing variables	
Wind speed	Monthly averages
Solar Radiance	Monthly averages
Water temperature	Measured at sampling time
Salinity	Measured at sampling time
Freshwater runoff, Q	Monthly totals
Internal variables	
Bottom water oxygen concentration [O ₂] _{bot}	Measured at sampling time (average for deepest 0.5m at each station)
Chlorophyll a concentration, [CHL]	Measured at sampling time

As part of the analysis the model parameters were tested to see if they varied significantly between stations, years and months. Where no significant differences were observed ($p > 0.05$) the model was reduced by setting the associated parameters to zero. For example, if the indicator was Secchi Depth and the variable was wind speed we might expect the coefficient in the model (K_{SD}) to be different depending on locality (station), due to the effects of wind on sediment resuspension being dependent on local geomorphology and water depth. However the coefficient might not necessarily be seasonally dependent. In this case K_{SD} would be different between stations and constant throughout the year.

After finding an appropriate and significant model the water quality indicators were adjusted to their co-variation with the physical forcing parameters and the effects on the residual variance assessed.

Results

Total Nitrogen (TN)

There was a general negative relationship between salinity and TN. This can be clearly seen in Fig. 2.32, where the annual averages for both TN and salinity at each station are plotted against each other. This relationship is also expected as freshwater run-off is the major source of N to the estuary. The most satisfactory model derived took into account the salinity relationship and a seasonal pattern.

$$TN = I_0 + I_{\text{month}} + K_s * \text{Salinity}, R^2 = 0.45$$

Model coefficients are presented in Appendix Table D.1. Fig. 2.33 shows the original and salinity-season adjusted annual means of TN. The adjusted mean values deviated between -10 to 18% of the original means. The standard error of the residuals was reduced from 26.9 $\mu\text{mol N l}^{-1}$ to 22.3 $\mu\text{mol N l}^{-1}$ (17% reduction).

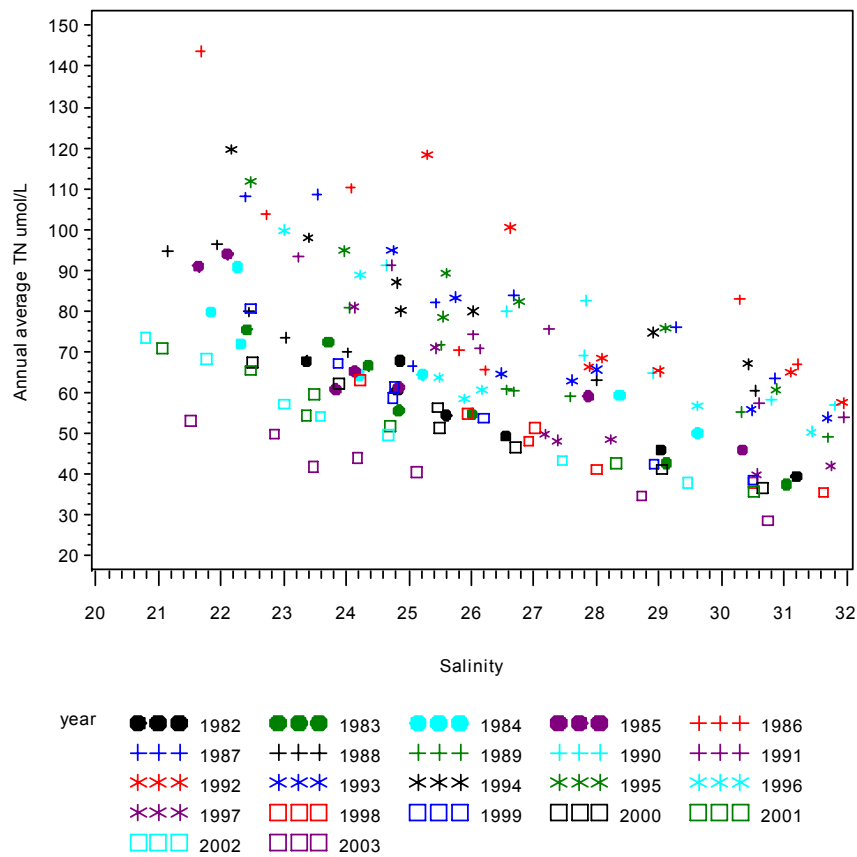


Fig. 2.32: Annual average TN concentrations against average salinity, revealing the apparent negative-linear relationship between TN and salinity.

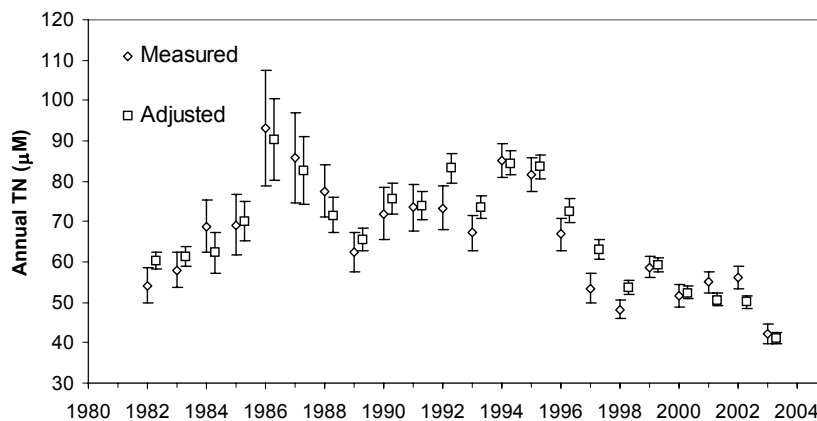


Fig. 2.33: The annual average TN concentrations in Limfjorden, measured and corrected for salinity (average: 26.2) co-variation and seasonal variation. The error bars show the 95% confidence of the means.

Total Phosphorus (TP)

TP concentrations have a very different seasonal pattern than TN. Although there were elevated concentrations during the winter months as a result of greater freshwater input (as seen for TN), the greatest concentra-

tions were usually measured in late summer (August and September). This is due to the fact that there are two sources of TP to the water column, terrestrial run off and sediment release during periods of anoxia (Fig. 2.31). The best model for TP was found when both of these sources could be represented.

Sediment release was best described by water temperature. The most satisfactory model derived was a model where the relationship with salinity was allowed to vary for each month and the relationship to temperature allowed varying between stations (basins). Additionally the salinity relationships were in two significantly different groups of stations; Skive-Lovns and Nissum-Kås-Thisted-Løgstør-Nibe. The model was

$$TP = I_0 + K_{s,m} * \text{Salinity} + K_{t,st} * \text{Temperature}, R^2 = 0.57$$

where the sub-script “m” refers to the month and “st” to the station. Model coefficients are presented in Appendix Table D.2. The original annual means and the salinity-temperature adjusted are shown in Fig. 2.34. The adjusted mean values differed from the measured means by –19 to 9%. The standard error of the residuals fell from 1.66 $\mu\text{mol P l}^{-1}$ to 1.12 $\mu\text{mol P l}^{-1}$, representing a 33% reduction.

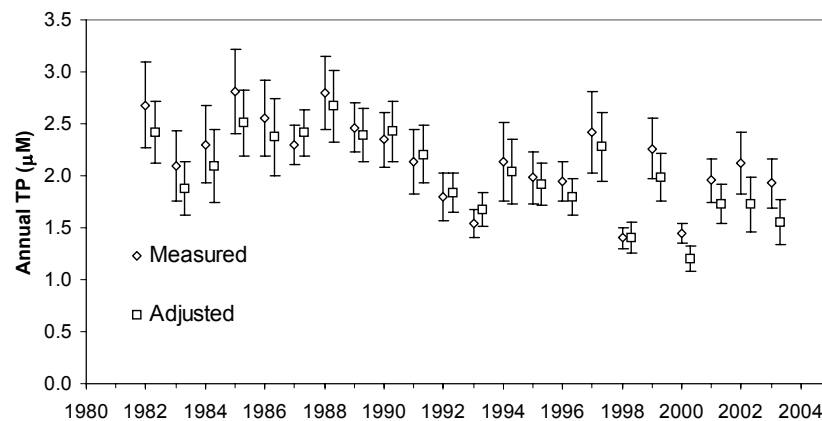


Fig. 2.34 The annual average TP concentrations in Limfjorden, measured and corrected for salinity (average 27.7) and temperature (average 10.1 °C) co-variation. The error bars show the 95% confidence of the means.

Chlorophyll concentration (CHL)

The seasonal means in the CHL in the estuary revealed that there is a fixed trend of a spring bloom in February-March followed by a late summer bloom. This general pattern is primarily driven by the availability of nutrients and light in the system. The spring bloom is initiated by increasing light levels and winter nutrients (i.e. nutrients from winter runoff), and becomes P limited during late spring and remains that way until low oxygen concentrations in bottom waters and sediments result in

a release of P from the sediments during late summer. The system then becomes primarily N limited. From this and from looking at Fig. 2.31 it is clear that many factors (both internal and external) influence CHL and this may make the modelling difficult.

The best model was found by taking into account a seasonal pattern and salinity fluctuations. The model was

$$\ln[\text{CHL}] = I_0 + I_{\text{month}} + K_s * \text{Salinity}, R^2 = 0.29$$

Model coefficients are presented in Appendix Table D.3. Fig. 2.35 presents the measured and adjusted annual mean CHL. The adjusted values differed by –29 to 17% from the measured means. The standard error of the residuals was reduced only slightly from 2.6 to 2.3 $\mu\text{g l}^{-1}$, representing a 12% reduction.

Secchi Depth (SD)

Variations in SD in the estuary are primarily driven by fluctuations in phytoplankton biomass (CHL) and sediment resuspension (represented by wind speed). Although a major fraction of downwelling light is attenuated by dissolved organic material, its effects on SD could be relatively constant throughout the year and across the estuary (in comparison to variability in chlorophyll), and therefore not explain much of the variability in SD. Wind speed was a significant parameter in the model and its coefficient was different between stations.

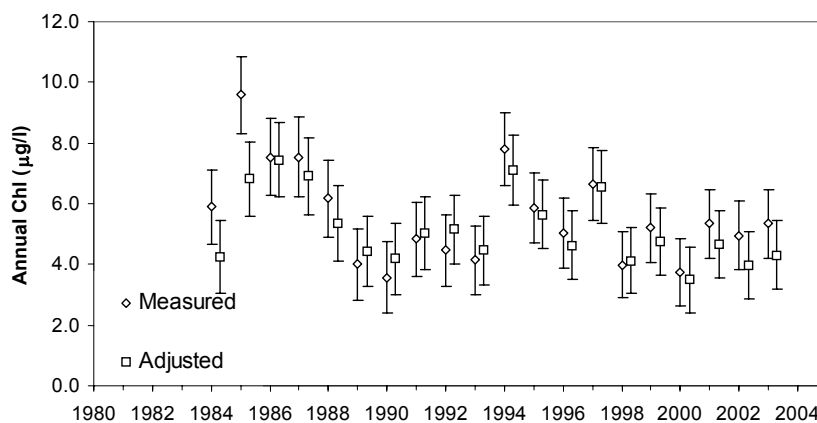


Fig. 2.35: The annual average CHL concentrations in Limfjorden, measured and corrected for seasonal (monthly) variability and salinity (average: 26.2) covariation. The error bars show the 95% confidence of the means.

The model was

$$\text{SD} = I_0 + K_{\text{chl,st}} * \ln(\text{CHL}) + K_{\text{w,st}} * \text{Wind Speed}, R^2 = 0.52$$

where the sub-script “st” refers to the station. Model coefficients are presented in Appendix Table D.4. The measured and adjusted annual mean SD are shown in Fig. 2.36.

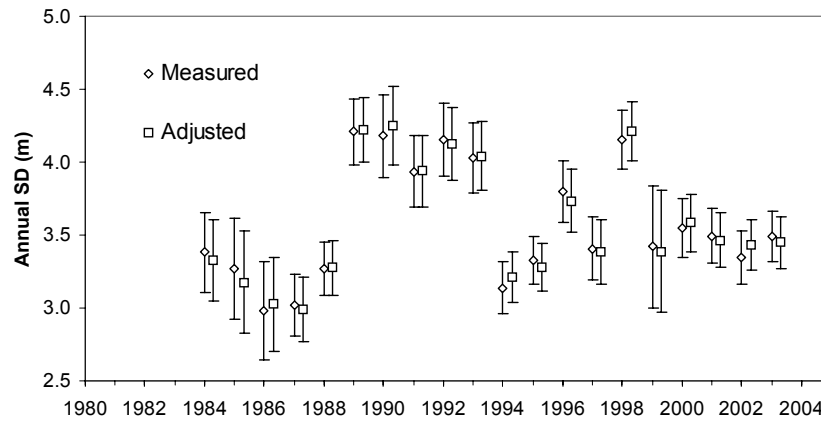


Fig. 2.36: The annual average SD concentrations in Limfjorden, measured and corrected for wind speed (average = 4.4 ms⁻¹) co-variation. The averages are not corrected for CHL as it is an internal variable. The error bars show the 95% confidence of the means.

Adjusted means differed from the measured means by –8 to 20%. The standard error of the residuals decreased noticeably from 1.7 to 1.2 m (28%) indicating an improvement in the precision of the annual means (when chlorophyll was included in the adjustment). Wind speed alone however offered little improvement in the precision of the annual means (compare error bars in Fig 2.36).

Discussion

A series of models have been derived and investigated for their ability to explain some of the natural variability in selected water quality parameters (TN, TP, CHL and SD). The models for SD, TN and TP could explain 52, 45 and 57% of the variability, respectively whereas the model for CHL was relatively poor (29%). The best increase in precision as a result of the co-variate normalisation was seen for TN concentrations. This most likely also reflects the fact that it also had a simple model and the most direct pathway (Fig. 2.31). Nitrogen supply to the estuary is dominated by freshwater runoff alone and could therefore be described by salinity variations. In contrast TP, CHL and SD are all influenced by a greater number of variables.

Variability in TP concentrations were driven by winter run-off (negative relation to salinity) and summer sediment release, parameterised by water temperature (positive relation) and differing between stations. A model with oxygen concentration in the bottom 0.5m of the water column instead of temperature gave similar results however explained slightly less of the variability ($R^2 = 0.53$). A better model was expected as low oxygen concentrations in the sediment and overlying water results in an

increased release of P from the sediments. A possible explanation for the poorer relationship obtained with oxygen could be that oxygen concentrations in Limfjord are widely variable on a short term basis due to a considerable oxygen demand in the sediments (negative effect) and wind driven complete vertical mixing of the whole water column (positive effect). For example during the summer day to day changes in wind speed can change the extent of oxygen deficiency very rapidly.

CHL concentrations had a seasonal dependency, most likely reflecting radiance levels and water temperature, and were negatively related to salinity. The salinity relation reflects that of nutrient concentrations. The results of the covariate analysis did not increase the precision of the annual chlorophyll means considerably. SD values were modelled well by CHL and wind speed. This was to be expected as algae blooms have significant effects on water clarity and in this relatively shallow estuary wind driven mixing can often lead to sediment resuspension and therefore influence SD. Even though both CHL and wind speed were significant parameters in the model, it was CHL that explained much of the variability in SD, on average, during the year. It is likely that the relative importance of these two parameters varies depending on season, with wind speed explaining much of the SD during the winter months and CHL during the summer months.

The results show that the environmental indicators that benefited most from this analysis were the annual mean values of TN and TP. This is most likely due to the fact that they are to a lesser extent influenced by short term climatic variability. Additionally the impacts of physical forcing could be largely explained by taking into account salinity variations.

2.6 Summary

The examples in Section 3 have shown that the residual variation in indicator variables in many cases can be reduced considerably by covariate normalization. The standard error of the residuals was in some examples reduced by up to ~80% (Gulf of Riga example), whereas in other cases only minor effects could be found (e.g. the Laajalahti and Vanhankau-punginlahti bays). In general the models best adapted to corrections in the examples of Section 3 reduced the standard error of the residuals by ~20%, which is a substantial increase in precision. The approach is clearly useful in retrospectively improving the precision of yearly averages in monitoring data. The gained increases in precision should however not be taken as an argument for decreasing monitoring intensity and coverage. The increases in precision are only possible when both covariates and indicator variables are representative of yearly or seasonal means and the data does not contain time lags obscuring their covariation. The seasonal production cycle is in this region generally the greatest cause of

variation. Sampling with a good geographic coverage and representation of the seasonal cycle therefore remains the only method to obtain representative yearly means. Without these prerequisites normalization may even become misleading.

The covariate correction should only remove residual between year variation and not actual trends in time that may occur in both the covariate, and the indicator variable. Great care should also be taken when including many covariates in the models, since the probability of including cross-correlated variables increases. The inclusion of internal variables should also be made with caution since it increases the risk of removing actual interannual differences occurring in both the covariate and the indicator variable. Increasing complexity level of the indicator variable also increases the number of covariates, which can be considered as internal. In general the most reliable results will be obtained by using very clear external forcing variables (e.g. wind, temperature, salinity etc.).

It is also important to identify the correct spatio-temporal scale for normalization with a particular purpose. The focus should always be to remove only what could be considered as residual variation, in relation to the scale of interest for the monitoring. For example the effects of a continuous increase in average yearly water temperature (e.g. global warming) or salinity (caused by e.g. land rise) should not be removed from an indicator variable by normalization to these covariates. Even if normalization in this case removes residual variation it would also remove actual trends in the indicator variable.

Systematic use of routinely monitored forcing variables has a considerable potential to increase the precision in indicator variables. In monitoring programs the simultaneous collection of such covariates should therefore be strongly encouraged. When localizing new stations for indicator variables it is important to consider the proximity to existing monitoring stations for external forcing variables. The technical development in automated collection of basic oceanographic, hydrological and atmospheric information is very rapid. It may in many cases be motivated to include such equipment for essential covariates in monitoring programs of biological variables if there is no existing station in the vicinity.

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3. Principles of classification

The European Water Framework Directive (WFD) states that the ecological status of water bodies should be classified according to a prioritised list of 1) biological elements, 2) chemical and physico-chemical elements, and 3) hydromorphological elements. The biological elements include phytoplankton, other aquatic flora and benthic invertebrates for marine water bodies as well as fish for water bodies characterised as transitional waters. Chemical and physico-chemical elements include water transparency, salinity, temperature, nutrients, oxygen and specific pollutants. Hydromorphological elements include depth variation, sediment, wave, tidal, and flow characteristics. Water bodies are classified into 5 categories according to a scheme for the 3 types of elements (Fig. 3.1).

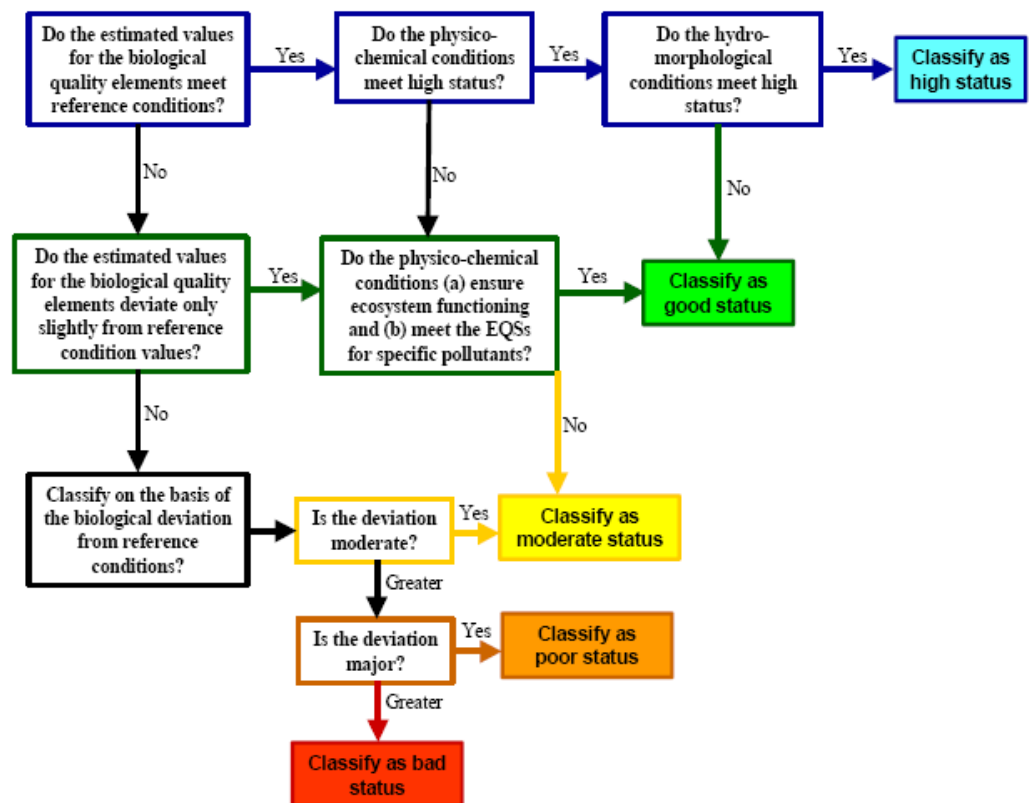


Fig. 3.1: Indication of the relative roles of biological, hydromorphological and physico-chemical quality elements in ecological status classification according to the normative definitions (from Anonymous 2003a).

Monitoring programs for WFD are to be operational in 2006 and observations from these monitoring programs should be compared against reference conditions. This is achieved by calculating an Ecological Quality Ratio (EQR) for each the different biological elements. In most situations EQR is a value between 0 and 1, where 0 represents the worst possible status and 1 represents reference conditions. Situations may occur where the actual situation is better than the reference condition values (EQR above 1 can be obtained). However, it should not be possible to obtain values of EQR below 0. In such cases the EQR can be reported by truncation as 0. Threshold values for the boundaries between the high and good, as well as good and moderate quality classes are to be determined in the intercalibration process to be finalised in 2006. If the high or moderate quality standards are not met for each of the biological elements, the ecosystem as a whole fails to meet the quality class requirements (one out, all out principle).

For the classification of biological and physico-chemical elements the ecological status is set to the lowest class of the elements. Thus, if phytoplankton and other aquatic flora meet a good status but benthic invertebrates only meet a moderate status, the overall biological status will be moderate (one out, all out principle). Moreover, the EC treaty states that the precautionary principle underpins all environmental legislation.

The biological and physico-chemical elements underlie large source of uncertainty, which can be partitioned into 1) spatial variations, 2) temporal variations, 3) sampling and analytical error in addition to the uncertainty introduced by the classification system. The confidence of classification should include classification, sampling and analytical errors only (Anonymous 2003a). Until there is a better understanding of spatial and temporal variability in the marine environment along with adequate marine biological quality control schemes, expert judgement will play an important role in classification.

In the guidance document for the implementation of the WFD precision is defined as the half-width of the confidence interval (Anonymous 2003b), and therefore the precision of classification depends on the confidence level chosen and the magnitude of random variation relative to the number of observations. Large uncertainties can be compensated by increased number of observations. The directive does not state any requirements with respect to required precision and confidence as well as how hypotheses of compliance should be tested (Anonymous 2003b).

There will always be situations where the actual ecological status cannot be determined with a given confidence, because the confidence interval is overlapping one or several boundaries on the EQR scale. In such cases it must be decided if the uncertainty should be to the benefit of the environment (fail-safe approach), to the benefit of the polluter (benefit-of-doubt approach), or shared equally between the two (face-value approach). These principles have been illustrated in Anonymous (2003b) in

the case of one boundary. The WFD has 5 classes separated by 4 threshold values. This implies that for

- *Fail-safe approach.* The value of the lower confidence limit for the EQR is used for classification, i.e. determines the quality class.
- *Benefit-of-doubt approach.* The value of the upper confidence limit for the EQR is used for classification.
- *Face-value approach.* The EQR value is used for classification.

The benefit-of-doubt approach actually has an administrative paradox included as the upper confidence limit for the EQR will be higher the less data it has been based on. Considering that administrative bodies are constantly under pressure to reduce monitoring efforts the implication of this approach could well be that monitoring is carried out to the minimum requirement of WFD (4 samples per year). It is also stated that the WFD is based on the precautionary principle and that the polluter should pay, and therefore it should be in the interest of the polluters to obtain sufficient precision. The extra costs of monitoring to reduce the risk of misclassification might therefore be justified in terms of ensuring that decisions to spend larger sums of money required for improvements are based on reliable information on status (Anonymous 2003b).

The logical consequence of these formulations is that the benefit-of-doubt approach should not be applied. The face-value approach (in the case of a median) can be considered as a special case of the fail-safe approach where the confidence is set to 50%. There is no incentive to increase the precision for the face-value approach, as increasing the number of samples will not affect the expected location of the median. The face-value approach implies that uncertainty will be equally shared between environment and polluter, whereas uncertainty will be to the benefit of the environment in the fail-safe approach and will place the burden of proof on the polluter. Thus, we recommend using the fail-safe approach with a pre-determined confidence level.

3.1 Statistical classification with covariables

In this chapter classification of indicators are considered without calculating the indicator into an EQR. The transformation and associated problems are discussed in section 4, where the reason for classifying on the indicator level is given. First we will consider classification without taking seasonal variation or covariables into account.

Let us assume that Y_i are monitoring data used for calculating an indicator for one of the biological elements having a true value of μ and deviations from this value are associated with the sampling. For simplicity let us further assume that these variations are normal, identical, inde-

pendently distributed, i.e. $Y_i \in N(\mu, \sigma^2)$. The “true” value of the indicator and the magnitude of the random variation are generally unknown, but can be estimated as

$$\hat{\mu} = \bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i \quad \text{and}$$

$$\hat{\sigma}^2 = s^2 = \frac{1}{n-1} \sum (Y_i - \bar{Y})^2$$

with a $1 - 2\alpha$ confidence interval for the estimator as

$$\left[\hat{\mu} + z_{\alpha} \cdot \sigma / \sqrt{n}; \hat{\mu} + z_{1-\alpha} \cdot \sigma / \sqrt{n} \right]$$

where z_x is the standard normal distribution value at x , if the true random variation is actually known or n is large, or

$$\left[\hat{\mu} + t(n-1)_{\alpha} \cdot s / \sqrt{n}; \hat{\mu} + t(n-1)_{1-\alpha} \cdot s / \sqrt{n} \right]$$

where $t(n-1)_x$ is the value at x of the t -distribution with $n-1$ degrees of freedom, if the random variation has to be estimated by the standard deviation s (small n). In practice, ecological classification will be a one-sided test using either the upper or the lower confidence limit, and $1 - \alpha$ denotes the confidence in a one-sided test.

Assume that boundaries between the 5 quality classes are known, $L_{HG} < L_{GM} < L_{MP} < L_{PB}$, then the fail-safe approach implies testing from the lowest ecological status (bad) towards the highest ecological status (high). This can be formulated as 4 sequential tests, where the next hypothesis is tested if the null hypothesis can be rejected:

- H0: Status is bad ($\mu \geq L_{PB}$) versus H1: Status is better than bad ($\mu < L_{PB}$)
- H0: Status is poor ($\mu \geq L_{MP}$) versus H1: Status is better than poor ($\mu < L_{MP}$)
- H0: Status is moderate ($\mu \geq L_{GM}$) versus H1: Status is better than moderate ($\mu < L_{GM}$)
- H0: Status is good ($\mu \geq L_{HG}$) versus H1: Status is high ($\mu < L_{HG}$)

Consequently, high ecological status can be demonstrated by rejecting all 4 null hypotheses. The null hypotheses are rejected if the upper confidence limit is below the boundary, e.g. for the first hypothesis if $\hat{\mu} + t(n-1)_{1-\alpha} \cdot s / \sqrt{n} < L_{PB}$. In practice, the testing of the 4 hypotheses for classification corresponds to identifying which class the upper confidence level belongs to. The testing implies that the true mean should actually be lower than the boundary by a margin of $t(n-1)_{1-\alpha} \cdot s / \sqrt{n}$ to reject the null hypothesis with sufficient confidence. This margin is equal to the precision of the estimated mean value as defined in the WFD moni-

toring guideline (Anonymous 2003b), and it can be seen that the precision varies with sample size n .

The lower confidence limit is the critical value under the null hypothesis, and the null hypothesis will be rejected if the indicator value is below this value (Fig. 3.2). This test is equivalent to testing if the upper confidence limit of the indicator is below the threshold L . Thus, given that the null hypothesis is actually true there is a probability ($\leq \alpha$) that the null hypothesis will be (falsely) rejected. However, there is similarly a probability, denoted β , of accepting the null hypothesis when it is not correct ($\mu < L$, as illustrated for a value μ_1 in Fig. 3.2). For small values of μ the probability of accepting the null hypothesis given that it is not correct (β) is small, whereas β increases as μ approaches L . The probability of rejecting the null hypothesis is called the power of the test ($1 - \beta$). Thus, the power is the proportion of the distribution for a given mean value that is below the critical value (Fig. 3.2).

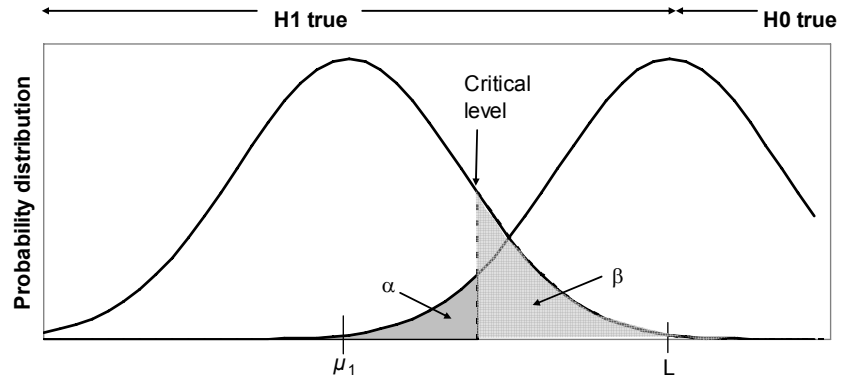


Fig. 3.2: Illustration of test of null hypothesis of $\mu > L$. The lower confidence limit of the distribution under the null hypothesis determines the critical value, and the proportion of the distribution for a given mean value, e.g. μ_1 , that is below the critical value determines the power of the classification.

Consequently, the probability of rejecting the null hypothesis (the power) in case the true mean of the indicator is μ can be calculated by means of the normal distribution function $N(\mu, \sigma^2)$

$$P\left\{\mu + z_{1-\alpha} \cdot \sigma / \sqrt{n} < L\right\} = \Phi\left(z_{\alpha} - \frac{\mu - L}{\sigma / \sqrt{n}}\right)$$

if the variance σ^2 is known, or by means of the non-central t-distribution

$$P\left\{t(n-1, \frac{\sqrt{n}}{\sigma}(\mu - L)) < t(n-1)_{\alpha}\right\}$$

if the variance is not known, but has to be estimated for the test statistics. For a given true mean value μ the power can be increased by increasing the sample size n or decreasing the variance σ^2 of the random variation

(Fig. 3.3). If the true value is equal to the boundary L there is only α probability of rejection, i.e. compliance of status. If the true mean value is close to L a large sample size is required, whereas less data is needed for mean values substantially lower than the boundary L . The power curve (Fig. 3.3) of the test statistic is also referred to as the operational characteristic of the test.

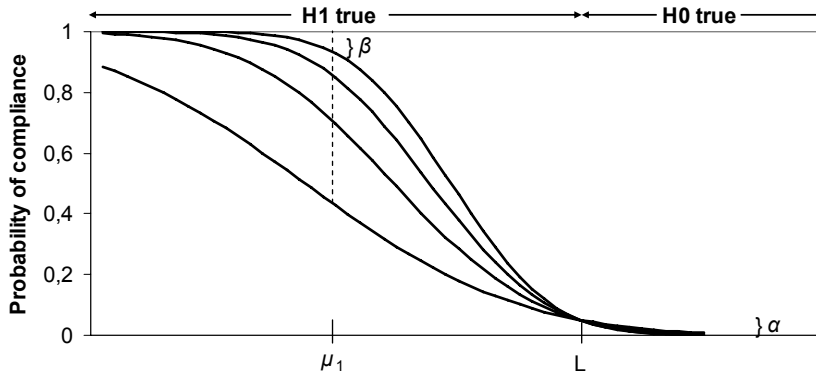


Fig.3.3: Power functions for rejecting the null hypothesis of $\mu > L$. Increasing n or decreasing σ^2 increases the probability of rejection (compliance of higher ecological status). A confidence level of 95% (one-sided) was chosen.

The steepness of the power curve is determined by the sample size for a fixed σ^2 , but normally the required number of samples is determined from specifications that the probability of compliance should be at least $1-\beta$ if the true mean is less than a specified value μ_1 . In statistics α and β give the values of the type I and type II errors, respectively, i.e. α is the probability of rejecting a true null hypothesis and β is the probability of accepting a false null hypothesis. For $\beta < 0.5$ the critical value of the test will be located between μ_1 and L . If the true variance σ^2 is known the required number of observations given values for α and β is

$$n \geq \left[\frac{(z_{1-\alpha} + z_{1-\beta}) \cdot \sigma}{L - \mu_1} \right]^2$$

and if the variance is unknown but estimated by s^2

$$n \geq \left[\frac{(t(n-1)_{1-\alpha} + t(n-1)_{1-\beta}) \cdot s}{L - \mu_1} \right]^2$$

In the latter case, the sample size appears on both sides and n must be determined iteratively by selecting an appropriate value for n and find the value that satisfies the inequality.

For design of monitoring programs in sensu WFD this implies determining confidence level ($1-\alpha$) and specification of power level ($1-\beta$) for a given value μ_1 for the indicator in question. In fact, the specification of μ_1 can be substituted by specifying the deviation from the boundary value $D = L - \mu_1$, which would lead to equal sample sizes for all 4 speci-

fied tests above, provided that the deviation specifications for the 4 tests are identical.

For the special case where data can be described by the lognormal distribution sample sizes can be determined from specification of the relative deviation d by means of

$$n \geq \left[(z_{1-\alpha} + z_{1-\beta}) \cdot \sigma / \log_e(1+d) \right]^2$$

for the case of known variance of the log-transformed data, and in cases, where the variance must be estimated, by

$$n \geq \left[(t(n-1)_{1-\alpha} + t(n-1)_{1-\beta}) \cdot s / \log_e(1+d) \right]^2$$

3.1.1 Standardisation

In the Phase B report methods and applications of covariate analysis were described to standardise an indicator variable to a given value of a covariate. In the following this is first presented for the case of a linear relationship to a covariate and subsequently for the more general case of including several covariates, both categorical and numerical.

Let us assume that our observations Y_i are dependent on the values of a covariate x_i , and that this dependency can be described by means of a linear regression. The linear model estimates are found by means of least squares regression, but are not shown here as the parameter estimates covariance matrix depend upon whether the model is formulated with or without subtracting the average of the covariate $\bar{x}$. For the purpose of standardisation, however, we are interested in predicting the mean and its confidence interval for a given value of the covariate x_s , and the formulation of the regression model does not change the formulas used for predictions. The expected value of the indicator corresponding to a given level of the covariate x_s is

$$\hat{\mu}_s = \hat{\alpha} + \hat{\beta} \cdot x_s$$

with a variance of

$$V[\hat{\mu}_s] = \sigma^2 \left[\frac{1}{n} + \frac{(x_s - \bar{x})^2}{\sum (x_i - \bar{x})^2} \right]$$

and consequently the $1 - 2\alpha$ confidence interval becomes

$$\left[\hat{\mu}_s + z_\alpha \cdot \sqrt{V[\hat{\mu}_s]}; \hat{\mu}_s + z_{1-\alpha} \cdot \sqrt{V[\hat{\mu}_s]} \right]$$

if the residual variation σ is known, and

$$\left[\hat{\mu}_s + t(n-2)_\alpha \cdot \sqrt{V[\hat{\mu}_s]}; \hat{\mu}_s + t(n-2)_{1-\alpha} \cdot \sqrt{V[\hat{\mu}_s]} \right]$$

if the residual variation is estimated. The implications for the required sample sizes are

$$n \geq \left[(z_{1-\alpha} + z_{1-\beta}) \cdot \sqrt{V[\hat{\mu}_s]} / (L - \mu_1) \right]^2$$

if the residual variation σ is known, and

$$n \geq \left[(t(n-2)_{1-\alpha} + t(n-2)_{1-\beta}) \cdot \sqrt{V[\hat{\mu}_s]} / (L - \mu_1) \right]^2$$

if the residual variation is estimated. It should be observed that sample size increases with $\sqrt{V[\hat{\mu}_s]}$, and therefore choosing a value for x_s deviating substantially from the bulk of x_i observations will increase the prediction variance and consequently the sample size n . Thus, it is important to choose a value for standardisation that is not deviating substantially from the monitoring data used for estimating the covariate relationship.

In the general case of standardisation it is assumed that the variations in Y_i can be described within the framework of general linear models, including multiple regression and analysis of variances. All explanatory variables, both categorical and numerical, are contained in the matrix $\underline{\underline{x}}$. The mean vector $\underline{\mu}$ and variance of the observation vector $\underline{Y}$ is formulated as

$$E[\underline{Y}] = \underline{\mu} = \underline{\underline{x}} \cdot \underline{\theta}$$

and

The parameters and the covariance matrix of the parameter estimates are found by least squares estimates,

$$\underline{\hat{\theta}} = (\underline{\underline{x}}' \underline{\underline{\Sigma}}^{-1} \underline{\underline{x}})^{-1} \underline{\underline{x}}' \underline{\underline{\Sigma}}^{-1} \underline{Y}$$

$$D(\underline{\hat{\theta}}) = \sigma^2 (\underline{\underline{x}}' \underline{\underline{\Sigma}}^{-1} \underline{\underline{x}})^{-1}$$

The expected value of Y for a given combination of explanatory variables can be estimated by formulating the standardised value for Y as a linear combination (contrast) of the parameter estimates.

$$\hat{\mu}_s = \underline{z}' \cdot \underline{\hat{\theta}}$$

with a variance of

$$V[\hat{\mu}_s] = \sigma^2 \underline{z}' (\underline{x}' \underline{\Sigma}^{-1} \underline{x})^{-1} \underline{z}$$

The confidence intervals similarly become

$$[\hat{\mu}_s + z_{\alpha/2} \cdot \sqrt{V[\hat{\mu}_s]}; \hat{\mu}_s + z_{1-\alpha/2} \cdot \sqrt{V[\hat{\mu}_s]}]$$

for known residual variance, and

$$[\hat{\mu}_s + t(n-k)_{\alpha/2} \cdot \sqrt{V[\hat{\mu}_s]}; \hat{\mu}_s + t(n-k)_{1-\alpha/2} \cdot \sqrt{V[\hat{\mu}_s]}]$$

if the residual variance is estimated, where k is the degrees of freedom used in the model (including the overall mean) equal to the number of free parameters in the model. The required sample sizes similarly become

$$n \geq \left[(z_{1-\alpha} + z_{1-\beta}) \cdot \sqrt{V[\hat{\mu}_s]} / (L - \mu_1) \right]^2$$

if the residual variance is known, and

$$n \geq \left[(t(n-k)_{1-\alpha} + t(n-k)_{1-\beta}) \cdot \sqrt{V[\hat{\mu}_s]} / (L - \mu_1) \right]^2$$

if the residual variance has to be estimated. For the lognormal distribution the required sample sizes are found by exchanging $(L - \mu_1)$ with $\log_e(1 + d)$. Most statistical computer packages include general linear models, but the factorisation of the $\underline{x}$ matrix may vary between products. This implies that the contrast vector $\underline{z}$ may appear differently depending on the specific software employed.

3.1.2 Multivariate distributions

The biological elements can be tested by means of several indicators, which may to some extent be correlated. For example, phytoplankton biomass can be measured as chlorophyll a or biovolume from microscopy analysis. Both of these variables express the same information, the amount of phytoplankton biomass. Another example could be nutrient conditions expressed by e.g. measured total nitrogen and total phosphorus concentrations. In general we may consider the k -dimensional observation vector

$$\underline{Y}_i = \begin{bmatrix} Y_{1i} \\ \vdots \\ Y_{ki} \end{bmatrix}$$

comprised of k different observations measured at the same time ($i=1\dots n$). The mean vector and dispersion matrix of $\underline{Y}$ can be estimated by

$$\hat{\underline{\mu}} = \bar{\underline{Y}} = \frac{1}{n} \sum_{i=1}^n \underline{Y}_i \quad \text{and}$$

$$\hat{\underline{\Sigma}} = \underline{S} = \frac{1}{n-1} \sum_{i=1}^n (\underline{Y}_i - \bar{\underline{Y}}) \times (\underline{Y}_i - \bar{\underline{Y}})'$$

Confidence levels for the mean vector are given by ellipsoids (illustrated for the two-dimensional case in Fig. 3.4) that can be calculated from the matrices above and the χ^2 -distribution, if the dispersion matrix is known, and the F-distribution, if the dispersion matrix is estimated by $\underline{S}$.

In the multivariate distribution boundaries are formulated as planes in the k -dimensional space, e.g. lines for the two-dimensional case (Fig. 3.4). Such planes can be formulated as a linear combination of the observation vector

$$\underline{a}'\underline{Y} = L_{HG}$$

and the classification reduces to testing hypotheses such as

$$H_0: \underline{a}'\underline{\mu} \leq L_{HG} \quad \text{versus the alternative } H_1: \underline{a}'\underline{\mu} > L_{HG}$$

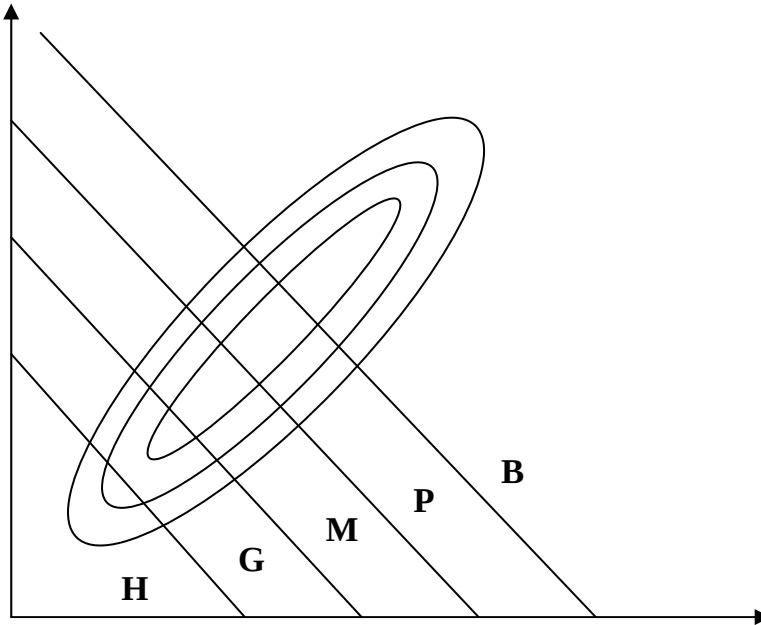


Fig. 3.4: A two-dimensional normal distribution for the mean vector $\underline{\mu}$ with contour ellipses for three different confidence levels of the distribution. Lines display the boundaries between the 5 ecological classes.

Testing of this hypothesis corresponds to calculating the proportion of the distribution of the mean vector that is below the plane defined by the null

hypothesis. The left hand side of H_0 is a contrast of the mean vector $\underline{\mu}$ with a variance of

$$V[\underline{a}'\underline{\mu}] = \frac{1}{n} \underline{a}'\underline{\Sigma}\underline{a}$$

and a corresponding confidence interval, if the dispersion matrix is known.

$$[\underline{a}'\hat{\underline{\mu}} + z_{\alpha/2} \cdot \sqrt{V[\underline{a}'\hat{\underline{\mu}}]}; \underline{a}'\hat{\underline{\mu}} + z_{1-\alpha/2} \cdot \sqrt{V[\underline{a}'\hat{\underline{\mu}}]}]$$

The required sample size is similarly found

$$n \geq \left[(z_{1-\alpha} + z_{1-\beta}) \cdot \sqrt{V[\underline{a}'\hat{\underline{\mu}}]} / (L - \underline{a}'\underline{\mu}_1) \right]^2$$

If the dispersion matrix is estimated from data (i.e. having a Wishart distribution) the confidence interval can be found as those $\underline{Y}$ on the linear projection $\underline{a}'\underline{Y}$ satisfying

$$\text{Wilk's } \Lambda < F(1, n-k)_{1-\alpha}$$

where the formula for Wilk's lambda can be found in most statistical textbooks on multivariate normal distributions (e.g. Anderson 1958). Consequently, there is no explicit formula for the required sample size n , which has to be found iteratively.

It can be advantageous to employ the multivariate classification method to synthesize the information from several similar measurement variables into a single test. However, only observations with all measurements available are used in the multivariate test statistics, and if there are frequent missing observations in the different measurement variables the resulting number of observation for use in the multivariate testing become sparse. In such cases, the multivariate approach should be abandoned or missing observations replaced by a robust method such as multiple imputation (Rubin 1987).

3.2 Classification using fuzzy logic

The fuzzy logic (FL) approach (Zadeh 1988, Dubois and Prade 1980) was initially attempted to apply within the project to derive Ecological Quality Ratio (EQR) algorithm for the west Estonian coastal waters as foreseen by the Water Framework Directive (WFD). FL is based on the notions of membership functions, logical operators and knowledge rules. Logical operators of the FL are well-known and widely used in the math Boolean operators and the knowledge rules, built on the Boolean logic,

are a kind of formalization of logical reasoning. Actually the only difference of the FL approach from the conventional mathematics arises from the uncertainty in determination of the membership function.

FL approach starts from the statement of classes to which certain phenomena belongs to a certain degree. The number of classes is larger than 1. A membership function (MF) is a function that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1 within each of the selected classes. The function input space is sometimes referred to in FL as the universe of discourse (similar to the domain of definition of a function in the conventional math). In the following the discussion is illustrated on an example of water quality indicators (concentrations) in a water body, e.g. a smoothly varying MF m in the class of high concentrations that passes from “less large” concentrations to larger concentrations of an indicator determining the water quality (Fig. 3.5). The output is a number known as the membership value m between 0 and 1. This function is supposed to define the transition from small to large concentration. Both indicated in the figure concentration values C_1 and C_2 are large to some degree, but one is significantly “less large” than the other.

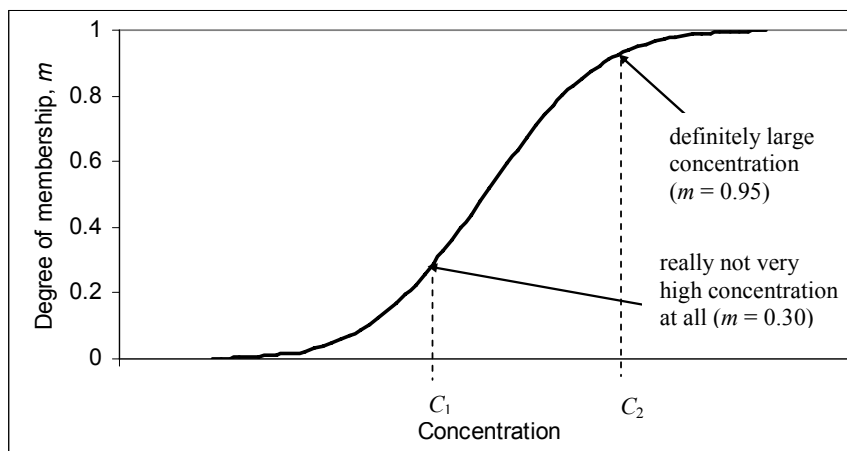


Fig. 3.5: Continuous membership function for the class 'large concentration'.

Now, suppose there is also a class of small concentrations and the associated MF (Fig. 3.6). Again, concentration values C_1 and C_2 are both small to some degree, but one is significantly “more small” than the other (Fig. 3.6). Actually indefinitely large number of different classes with the relevant arbitrary MF (e.g. bell-shaped) is allowed to introduce.

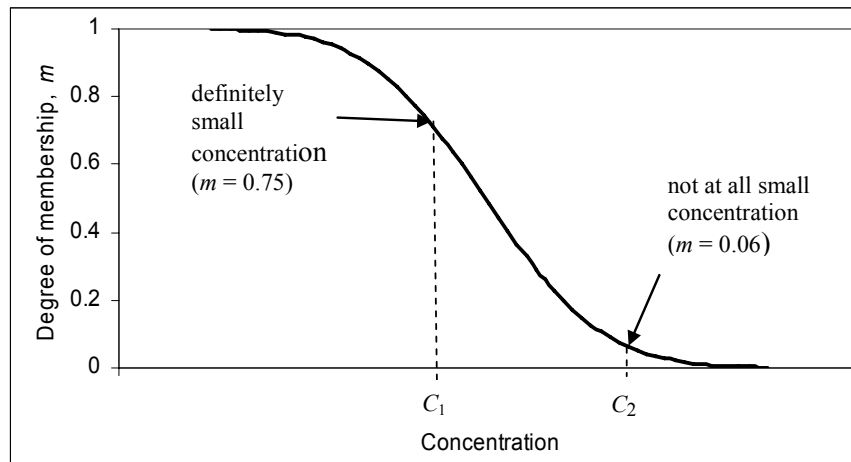


Fig. 3.6: Continuous membership function for the class 'small concentration'.

A simplified example diagram of application of FL to the water quality classification is shown in Fig. 3.7. The water quality index or aggregated output in the right bottom corner of the diagram is supposed to be determined by two water quality indicators, concentrations x and y . Each row of the graph corresponds to one knowledge rule of the Boolean logic 'if...and/or...then...', where logical operators 'and' and 'or' are prescribed the meaning of minimum and maximum operators respectively. The first column of graphs in Fig. 3.7 presents the input x fuzzification via the respective MF-s in classes of large concentration (topmost graph) and small concentration (bottom graph). The second column shows the input y fuzzification in the defined three classes of large, average and small concentrations. The third column shows particular (arbitrary again) output MF-s to which the knowledge rule outputs are applied (or implicated in the FL terms) in the fourth column. Finally, the 'implicated' particular outputs in the fourth column are combined as shown in the rightmost bottom graph and the aggregated terminal output serving as the water quality index or EQR value is obtained through the so-called 'defuzzification' as e.g. weighted average of the final shape.

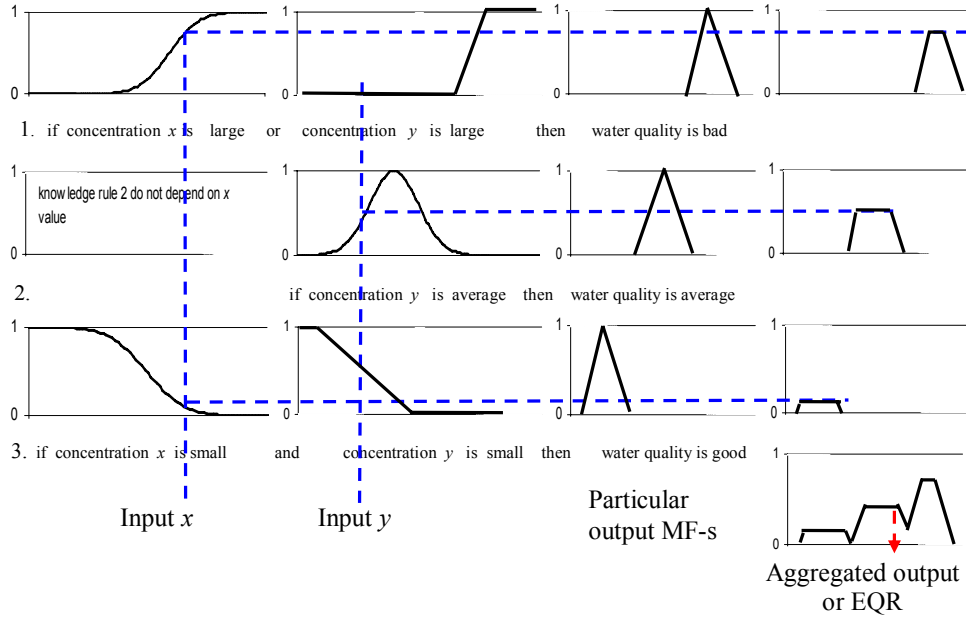


Fig. 3.7: Simplified example diagram of possible application of FL to the water quality classification.

FL presumes the membership function as an arbitrary function defined in respect to some application as suitable from the point of view of “simplicity”, “convenience”, “speed”, and “efficiency”, though all these good qualities remain again undefined. The only restriction set for the membership function is that its values must remain within interval $[0, 1]$. So, the membership functions have no physical essence whatsoever and the suitability of the full construction of the “fuzzy model” is judged on the basis of satisfactory procedure output in special cases. The problem is that having not precisely defined the very basic physical essence of the approach, the constructed FL decision making system would unavoidably obtain an ad hoc character, which does not necessarily ensure reasonable results for the changed initial conditions and, what is crucial, the reason of the constructed system failure cannot be detected unambiguously, the system can be improved only by the “try and failure” method. The classical FL approach as essentially linear does not also allow for inclusion into the derivation of EQR (as the response) of the quantitative information on the covariance of the water quality determining indicators and their covariates as predictors. Though, the inclusion of the information on the covariance of water quality indicators and their covariates estimated on the bases of actual measured data into the determination of the EQR was one of the central ideas of the current project approach.

Due to the uncertainty in determination of FL membership functions and, as a consequence, of the knowledge rules as inherent constituents of the FL, it was found that any EQR algorithm based solely on the FL would lack some basic properties (e.g. uniqueness and universality) re-

quired by any index aggregating information on water quality multiple indicators. Therefore, it was decided to continue the elaboration of the EQR on more firm grounds as based on the water quality indicators and their covariates as statistically dependent random quantities, fully determined by their joint multivariate probability distribution.

3.3 Classification in an EQR framework

Indicators used for classification should be transformed into an EQR scale by means of a stated reference condition. The EQR shall represent the relationship between values of the measurement variable and the reference condition of this variable on a scale between 0 and 1, where values close to 0 represent bad status and values close to 1 represent high status.

3.3.1 Transformations to EQR scale

Let $\hat{\mu}$ be the estimated indicator value within the sample space $[a;b]$, where a and b represent values for the reference conditions at bad and good status, respectively, and let $f(\hat{\mu})$ be the monotonous and continuous transformation that maps $\hat{\mu}$ onto an EQR scale such that $f(a)=0$ and $f(b)=1$. Several transformations can be employed depending on the indicator sample space.

Linear transformations

The linear transformation translate estimated mean levels of the indicator proportionally to an EQR scale by

$$EQR = \frac{\hat{\mu} - a}{b - a}$$

or in the truncated form (truncated around a and b)

	if $a < b$ (ecological status improves with increasing $\hat{\mu}$)	if $a > b$ (ecological status declines with increasing $\hat{\mu}$)
$EQR = \begin{cases} 0 & \text{if } \hat{\mu} \leq a \\ \frac{\hat{\mu} - a}{b - a} & \text{if } a < \hat{\mu} < b \\ 1 & \text{if } \hat{\mu} \geq b \end{cases}$		$\begin{cases} \text{if } \hat{\mu} \geq a \\ \text{if } a > \hat{\mu} > b \\ \text{if } \hat{\mu} \leq b \end{cases}$

or in the piecewise linear form

$$EQR = \begin{cases} 0 & \text{if } \hat{\mu} \leq a \\ \frac{\hat{\mu} - a}{c - a} \cdot EQR(c) & \text{if } a < \hat{\mu} < c \\ \frac{\hat{\mu} - c}{d - c} \cdot (EQR(d) - EQR(c)) + EQR(c) & \text{if } c < \hat{\mu} < d \\ \vdots & \vdots \\ \frac{\hat{\mu} - f}{b - f} \cdot (1 - EQR(f)) + EQR(f) & \text{if } f < \hat{\mu} < b \\ 1 & \text{if } \hat{\mu} \geq b \end{cases} \quad \begin{array}{l} \text{if } a < b \\ \text{if } a > b \end{array}$$

where EQR values have been fixed for a number of levels (c, d, e, f in Fig. 3.8). For the transformations shown above, EQR is increasing with indicator level. In the case of the A special cases of the linear transformations is $a=0$ (the indicator has a value of zero at bad status), where indicator levels are scaled by the reference condition. The linear transformations can be applied to all indicator values, both negative and positive values.

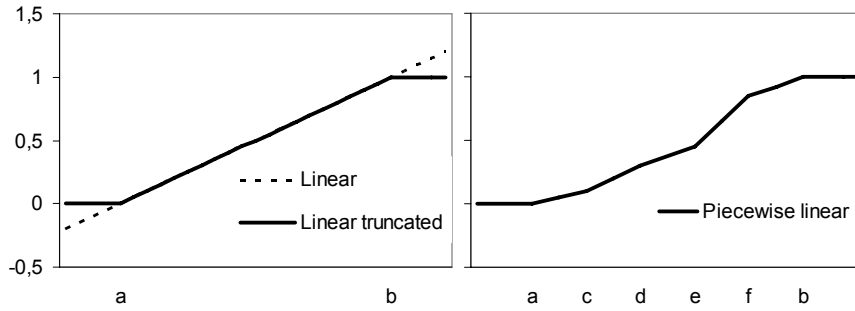


Fig. 3.8: Linear transformations of an indicator level to the EQR scale.

Log-linear transformation

The log-linear transformation is similar to the linear transformation except that values on the indicator axis have been log-transformed before transformation (Fig. 3.9).

$$EQR = \frac{\log(\hat{\mu}) - \log(a)}{\log(b) - \log(a)}$$

It should be stressed that a and b can only take positive values, and that values of $\hat{\mu}$ outside the interval $[a; b]$ will result in values larger than 1 or less than zero, i.e. the transformation would have to be truncated.

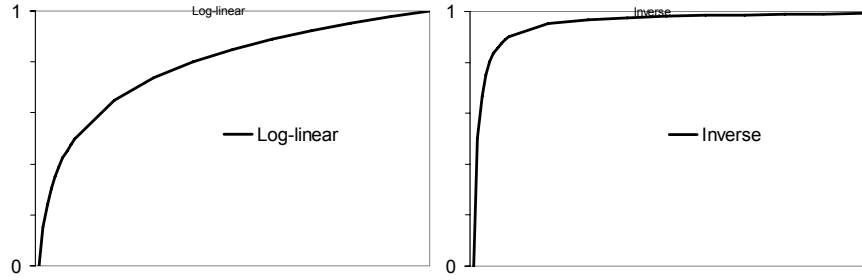


Fig. 3.9: Log-linear and inverse transformations of an indicator level to the EQR scale.

Inverse transformation

The inverse transformation can similarly be adjusted to take the appropriate values for $\hat{\mu} = a$ and $\hat{\mu} = b$ (Fig. 3.9).

$$EQR = \frac{a \cdot b}{(a - b) \cdot \hat{\mu}} - \frac{b}{a - b}$$

with the requirement that $a, b \neq 0$ and that a and b are either both positive or negative, i.e. $\hat{\mu}$ cannot take zero value.

A special case of the inverse transformation is $a = \infty$ that results in

$$EQR = \frac{b}{\hat{\mu}}$$

i.e. reference condition divided by the actual state.

Summary of transformations

Although all transformations are flexible and can be adjusted to accommodate the appropriate EQR values for high and bad ecological status, both the log-linear and the inverse transformation have problems if ranges of the sample space include zero (Table 3.1). Moreover, both the log-linear and the inverse transformation have strong gradients for values near a , a feature that can be mimicked by the piecewise linear transformation, if desired.

Overall, the linear and the piecewise linear transformation provide sufficient flexibility for calculating appropriate EQR values corresponding to the appropriate indicator values, and these transformations are rather simple, logically interpretable and easy to compute. Consequently, it is recommended to employ the linear or the piecewise linear transformation for calculating the EQR based on the estimated indicator level $\hat{\mu}$.

Table 3.1: Overview of the applicability of transformations.

Sample space	Linear	Piecewise linear	Log-linear	Inverse
$]-\infty; -\infty[$	OK	OK		
$[0; -\infty[$	OK	OK		
$]0; -\infty[$	OK	OK	OK	OK
$[a; b]$ both pos.	OK	OK	OK	OK
$[a; b]$ both neg.	OK	OK		OK
a neg.; b pos.	OK	OK		

Furthermore, it is recommended to use these linear transformations such that the boundary between high and good is represented by the EQR value of 0.8, the boundary between good and moderate by the EQR value of 0.6, and so forth. This will improve the general understanding of the link between EQR value and classification.

3.3.2 Effect of precision on EQR scale

If the simple linear transformation without truncation is applied to an indicator, both the mean and the confidence limits can be scaled by the transformation. This implies that if the indicator value is normal distributed, so will the transformed variable on the EQR scale be normal distributed with a symmetrical confidence interval. For any other chosen transformation this will not be the case. The truncated linear transformation or the piecewise linear transformation will either condense or expand the distribution on either sides of the change-points (Fig. 3.10). This implies that the mean value on the indicator scale cannot implicitly be transformed to the EQR scale by these transformations.

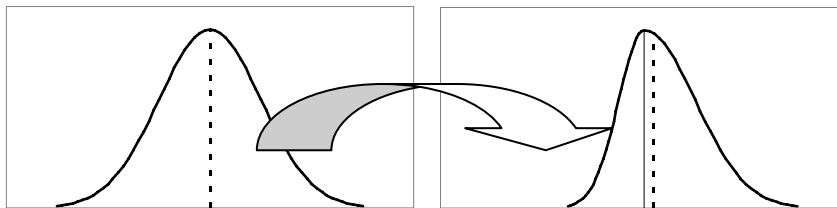


Fig. 3.10: The effect of non-linear transformation (ex. piecewise linear) on a normal distribution. Dotted lines indicate the location of the means in the original and transformed distribution, which for the latter is different from the transformation of the mean value shown by the thin solid line.

In addition, the distribution after transformation to the EQR scale does not have well-defined mathematical properties with explicit formulas for calculating the mean, except in the special cases of the linear and logarithmic transformations. The logical conclusion is to use the backward transformation $f^{-1}(\hat{\mu})$, which is well-defined since $f(\hat{\mu})$ is monotonous and continuous, to compute the equivalent of the boundaries between ecological status classes on the indicator scale, and employ these boundaries for classification on the indicator scale as described in Section 2. This implies that levels of precision will be described for the indicator, but

what level of precision is actually required to obtain a reasonable classification?

In order to address this question, consider the precision of an indicator on the EQR scale after linear transformation. The ideal case is a relative precision close to zero which will yield a nearly perfect classification, as opposed to a relative precision of e.g. 0.5 where the confidence levels may stretch over the entire EQR scale (Fig. 3.11).

Assuming the 5 status classes have an equal width on the EQR scale (0.2 per class), confidence levels of the indicator will span this width if the relative precision is 0.1, remembering that the guidance documents to the WFD (Anonymous 2003b) define precision as the half-width of the confidence interval. Thus, it is possible to obtain one unique classification irrespective of the chosen principle for classification taking uncertainty into account (Section 3.1) if the relative precision is less than 0.1, whereas this will not be the case for relative precisions above 0.1. Therefore, we suggest that sample sizes for monitoring programs should be determined to assure a relative precision of less than 0.1 on the indicator value. Although the requirement on precision does not involve specification of power for a given mean level of μ_I , the symmetry of the distribution and the required fixed relative precision of 0.1 corresponds to setting $\beta=\alpha$ and $|L-\mu_I|$ equal to 0.2 on the EQR scale using the formulas for n in the first section of this chapter.

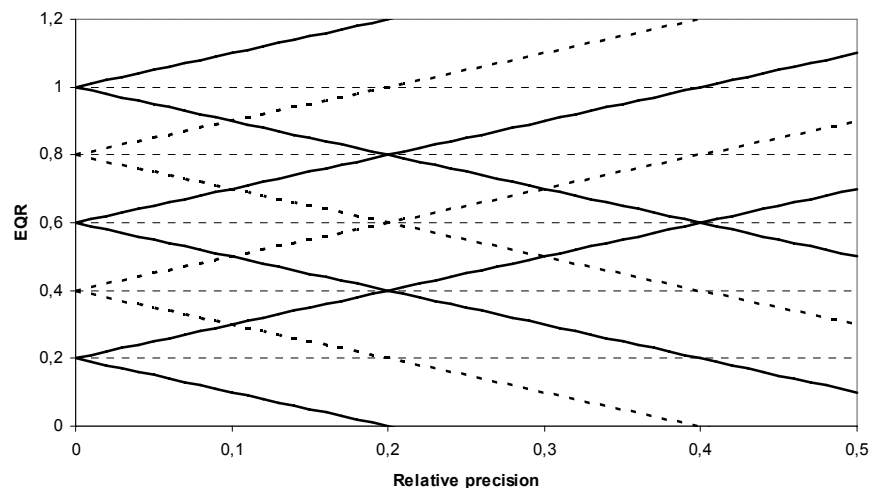


Fig. 3.11: Confidence levels for 5 indicator values with means equal to 20%, 40%, 60%, 80% and 100% of the reference condition with increasing relative precision (precision/mean value).

Alternatively, power requirements for μ_I can be specified. For example, if the mean value of the indicator is equal to the midpoint of an EQR interval (e.g. $L=0.4$ and $\mu_I=0.5$) and α and β are set to the standard values of 0.05 and 0.2, respectively, then this would lead to more than twice as large a sample size. In fact, all power levels above 50% ($\beta < 0.5$) at the midpoint will result in larger sample sizes. Considering that a probability

of 80% for accepting that the mean is above L given that it actually is 10% above on the EQR scale appears to be a reasonable requirement, the stated relative precision of 10% should be seen as an absolute maximum.

3.4 Summary

For the classification of an indicator (univariate or multivariate) the following steps should be carried out:

- Set the confidence used for classification ($1-\alpha$). It is recommended to use the fail-safe approach with commonly applied confidence level of 95%.
- Reference conditions and boundaries between ecological status classes are determined on the indicator scale.
- Calculate the confidence interval of the indicator by the formulas above taking into account whether the random variation is estimated or assumed known, and including potential covariates.
- If ecological status increases with the indicator value, determine the lower confidence level and use this as a test statistic for classification, i.e. assessing the location of the mean with a certain confidence. If ecological status decreases with the indicator value, determine the upper confidence level and use this value for classification.

For determining the appropriate number of samples for ecological status assessment the following steps should be carried out:

- Determine the confidence used for classification ($1-\alpha$).
- Determine the required precision of the indicator. It is recommended to have a relative precision no larger than 0.1 on the EQR scale. For sample size calculations set $\beta=\alpha$ and $|L-\mu_I|=0.2$ on the EQR scale.
- or
- Determine the required power ($1-\beta$) for a value μ_I exceeding the boundary L . Suggested values are $\beta=0.2$ and the equivalent of $|L-\mu_I|$ to 0.1 on the EQR scale.
- Calculate sample sizes according to formulas in Section 2.

In Section 2 formulas were given that either assumed the random variance known or to be estimated from data. In most situations the magnitude of the random variation is not known but it has to be estimated. However, in many situations long-term time series, extending much further than the period of assessment, are available and can be used for estimating the variance, provided that trends and seasonality are accounted for in the model. If such time series consists of more than 50 observations then the standard error σ is reasonably well approximated by the standard

deviation s of the residuals. Thus, it is recommended to use long-term time series, if available, to estimate the magnitude of the random variation.

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4. Monitoring designs for classification

The essential question when design monitoring program for ecological status classification is: how many stations and which sampling frequency? However, the actual location of monitoring stations is also an important issue. The statistical classification methodology described in the previous chapter gives a rigid and objective framework for determining sample sizes based on specifications of permissible deviations from a boundary, whereas the location of sampling points is more subjective. Often the location of stations is dictated more by rules of thumb, professional judgment and logistics in relation to monitoring cruises. Based on the results from the previous chapters some comments can be addressed to the location of monitoring stations.

The prime characteristic of stations is that they shall represent the water body. In case of a single station it is common to place it “in the middle”, where middle is subjectively chosen from inspection of maps as a mid-point that “minimizes the sum of distances from all possible locations to that given point”. Although this problem may also be solved more objectively by mathematical optimisation of such a criterion, it is not entirely clear what the benefit would be from an ecological point-of-view. In particular, mid-points from an areal investigation does not necessarily represent an average water mass. The problem does not get easier in case of several stations.

Estuaries and to some extent also coastal ecosystems are characterised by mixing of two water masses, and salinity is the conservative tracer used to characterise water samples. The average salinity of a water body can be determined from a hydrodynamical model and similarly, the indicator value corresponding to that average water mass can be found provided that observations covariate with salinity (see Chapter 2). If this is the case it is beneficial to locate stations such that they represent the entire salinity gradient in order to obtain a salinity relationship as precise as possible.

In this chapter we will employ the formulas derived in Chapter 3 to the 7 case study areas in order to obtain estimates of required number of samples to correctly classify a water body if the true mean deviates with a specified value from the boundary of interest, i.e. in practice the boundary between good and moderate.

4.1 Sample sizes

Traditionally sample sizes have not been determined from statistical principles and analyses of the magnitude of random variation. This is also the case of the directive itself (Anonymous 2000) which indicates monitoring frequencies of 4 times per year for nutrients and 2 times per year for phytoplankton without any specification of the required number of monitoring stations. Most experts in marine science and monitoring would render these frequencies inadequate for classification, and this was also acknowledged in the Common Implementation Strategy guidelines (Anonymous 2003) that recommended biweekly or monthly sampling although this recommendation was not based on statistical analyses.

In Chapter 3 the following equation for calculating the required number of samples was given

$$n \geq \left[(z_{1-\alpha} + z_{1-\beta}) \cdot \sqrt{V[\hat{\mu}_s]} / (L - \mu_1) \right]^2$$

assuming that the residual variance has been estimated on a relatively large data set, such that the percentiles of the normal distribution apply. In principle this relationship has two unknown if standard values for the significance level ($\alpha=0.05$) and the power level ($\beta=0.2$) are chosen. If a permissible tolerance for the classification, $d = L - \mu_1$, is given then minimum sample sizes can be found. Alternatively, if the number of samples is given then minimum deviations, d , from a boundary can be calculated in order to obtain a correct classification with a reasonable probability.

$$d \geq (z_{1-\alpha} + z_{1-\beta}) \cdot \sqrt{\frac{V[\hat{\mu}_s]}{n}}$$

For most indicators it is preferable to work with relative deviations, $d' = d/\mu$, instead of absolute deviations, as boundaries between status classes change relative to the absolute values of the indicator. For example, differences in boundaries for water transparency may be around 1 m at open water sites with clear water (~ 10 m), whereas differences between boundaries in more turbid waters (secchi depths ~ 1 m) may be around 0.1 m, i.e. in both cases approximately 10% of the expected value. The required number of observations in order to detect a relative deviation from a boundary of d' with a probability of $1-\beta$ can thus be found as

$$n \geq \left[(z_{1-\alpha} + z_{1-\beta}) \cdot CV / d' \right]^2$$

where CV is the coefficient of variation for the residuals after the covariation analysis. Similarly, the relative minimum deviation can be found as

$$d' \geq (z_{1-\alpha} + z_{1-\beta}) \cdot \frac{CV}{\sqrt{n}}$$

In the following sample sizes are calculated for the different indicators and different study areas.

4.1.1 Chlorophyll *a*

Covariation analyses were carried out for 6 of the study areas resulting in 10 estimates of the residual variation, because the analyses also were conducted for specific sites within the chosen areas. The relative magnitude of the random variation (CV) varied from 12.8% in the central part of the Curonian Lagoon to 55.8% in Moonsund (Table 4.1). If a deviation from a boundary of 5% should be detected with a probability of 80% the required number of observations range from about 50 to 1000. It is also seen that the required number of observations decreases with d' . Most of the analysed sites had CV s above 30%, and given that the potential risk of overfitting data at sites with fewer data and thereby obtaining a too low estimate of the random variation, CV values are to be expected in the range 30-60% at non-analysed sites.

Table 4.1: Coefficients of variation for chlorophyll *a* and calculated sample sizes for relative deviations from a boundary to be detected with a power of 80%.

Site	CV	$d'=0.05$	$d'=0.10$	$d'=0.15$	$d'=0.20$
Askö	32.4%	301	75	33	19
Lahajalahti	14.0%	56	14	6	4
Vanhankaupunginlahti	32.0%	294	74	33	18
Moonsund	55.8%	895	224	99	56
GoR Sandy	46.2%	613	153	68	38
GoF Stony	58.5%	984	246	109	62
GoR Trans	45.3%	590	148	66	37
Curonian Northern Lagoon	16.1%	74	19	8	5
Curonian Central lagoon	12.8%	47	12	5	3
Limfjorden	46.0%	609	152	68	38

With monthly or biweekly sampling as recommended in Anonymous (2003) relative deviations from a boundary L on the order of 10-45% can be detected for monthly sampling and 7-31% for biweekly sampling if the indicator is calculated for a single station in a single year (Table 4.2). The relative deviation to be detected, d' , decreases if more years or stations are used for calculating the indicator. If 3 years with a single station or 3 stations in a single year is used then deviations of 6-26% can be detected with monthly sampling, and 7-31% can be detected with biweekly sampling.

These values could be compared to the deviation from the reference condition to the boundary between good and moderate ecological status, which is expected to be 25-50% (see Chapter 1). Given this the recommendation of biweekly or monthly sampling is not a case of oversampling.

Table 4.2: The relative deviation (d') that can be detected with a probability of 80% with monthly sampling (12 per year) or biweekly sampling (26 samples per year). n is the number of stations or years used for calculating the indicator.

Site	Monthly sampling			Biweekly sampling		
	$n=1$	$n=2$	$n=3$	$n=1$	$n=2$	$n=3$
Askö	0.25	0.18	0.14	0.17	0.12	0.10
Lahajalahti	0.11	0.08	0.06	0.07	0.05	0.04
Vanhankaupunginlahti	0.25	0.18	0.14	0.17	0.12	0.10
Moonsund	0.43	0.31	0.25	0.29	0.21	0.17
GoR Sandy	0.36	0.25	0.21	0.24	0.17	0.14
GoF Stony	0.45	0.32	0.26	0.31	0.22	0.18
GoR Trans	0.35	0.25	0.20	0.24	0.17	0.14
Curonian Northern Lagoon	0.12	0.09	0.07	0.08	0.06	0.05
Curonian Central lagoon	0.10	0.07	0.06	0.07	0.05	0.04
Limfjorden	0.36	0.25	0.21	0.24	0.17	0.14

4.1.2 Secchi

Covariation analyses were carried out for 4 of the study areas resulting in 6 estimates of the residual variation, because the analyses also were conducted for specific sites within the chosen areas. The relative magnitude of the random variation (CV) varied from 16.8% at Askö to 34.3% in Limfjorden (Table 4.3).

If a deviation from a boundary of 5% should be detected with a probability of 80% the required number of observations range from about 80 to over 300. The estimated CV values were lowest at more open water sites and increasing for sites with more estuarine character. CV values may be chosen in these ranges for non-monitored sites depending on the specific character of the site.

Table 4.3: Coefficients of variation for secchi depth and calculated sample sizes for relative deviations from a boundary to be detected with a power of 80%.

Site	CV	$d'=0.05$	$d'=0.10$	$d'=0.15$	$d'=0.20$
Askö	16.8%	81	20	9	5
Lahajalahti	18.8%	101	25	11	6
Vanhankaupunginlahti	34.0%	332	83	37	21
Curonian Northern Lagoon	23.3%	157	39	17	10
Curonian Central lagoon	25.0%	180	45	20	11
Limfjorden	34.3%	338	85	38	21

With monthly or biweekly sampling as recommended in Anonymous (2003) relative deviations from a boundary L on the order of 13–27% can be detected for monthly sampling and 9–18% for biweekly sampling if the indicator is calculated for a single station in a single year (Table 4.2).

The relative deviation to be detected, d' , decreases if more years or stations are used for calculating the indicator. If 3 years with a single station or 3 stations in a single year is used then deviations of 6–26% can be detected with monthly sampling, and 7–31% can be detected with bi-weekly sampling. These values could be compared to the deviation from the reference condition to the boundary between good and moderate ecological status, which is expected to be 25–50% (see Chapter 1). It is therefore recommended to use several stations or several years for calculating indicators of water transparency.

Table 4.4: The relative deviation (d') that can be detected with a probability of 80% with monthly sampling (12 per year) or biweekly sampling (26 samples per year). n is the number of stations or years used for calculating the indicator.

Site	Monthly sampling			Biweekly sampling		
	$n=1$	$n=2$	$n=3$	$n=1$	$n=2$	$n=3$
Askö	0.13	0.09	0.07	0.09	0.06	0.05
Lahajalahti	0.15	0.10	0.08	0.10	0.07	0.06
Vanhankaupunginlahti	0.26	0.19	0.15	0.18	0.13	0.10
Curonian Northern Lagoon	0.18	0.13	0.10	0.12	0.09	0.07
Curonian Central lagoon	0.19	0.14	0.11	0.13	0.09	0.08
Limfjorden	0.27	0.19	0.15	0.18	0.13	0.10

4.1.3 Total nitrogen

Covariation analyses were carried out for all study areas resulting in 11 estimates of the residual variation, because the analyses also were conducted for specific sites within the chosen areas. The relative magnitude of the random variation (CV) varied from 4.7% at Askö to 37.2% in Limfjorden (Table 4.5). If a deviation from a boundary of 5% should be detected with a probability of 80% the required number of observations range from about 10 to almost 400. Given that the potential risk of over-fitting data at sites with fewer data and thereby obtaining a too low estimate of the random variation, CV values are to be expected in the range 20–40% at non-analysed sites.

Table 4.5: Coefficients of variation for total nitrogen and calculated sample sizes for relative deviations from a boundary to be detected with a power of 80%.

Site	CV	$d'=0.05$	$d'=0.10$	$d'=0.15$	$d'=0.20$
Oslo Fjord	23.0%	152	38	17	10
Askö	4.7%	6	2	1	0
Lahajalahti	7.2%	15	4	2	1
Vanhankaupunginlahti	13.1%	49	12	5	3
Moonsund	34.1%	333	83	37	21
GoR Sandy	7.3%	15	4	2	1
GoF Stony	12.1%	42	11	5	3
GoR Trans	6.9%	14	3	2	1
Curonian Northern Lagoon	30.7%	271	68	30	17
Curonian Central lagoon	27.0%	209	52	23	13
Limfjorden	37.2%	397	99	44	25

With monthly or biweekly sampling as recommended in Anonymous (2003) relative deviations from a boundary L on the order of 4-29% can be detected for monthly sampling and 2-20% for biweekly sampling if the indicator is calculated for a single station in a single year (Table 4.6). The relative deviation to be detected, d' , decreases if more years or stations are used for calculating the indicator. If 3 years with a single station or 3 stations in a single year is used then deviations of 2-17% can be detected with monthly sampling, and 1-11% can be detected with biweekly sampling. These values could be compared to the deviation from the reference condition to the boundary between good and moderate ecological status, which is expected to be 25-50% (see Chapter 1). Total nitrogen is one of the less variable monitoring parameters and therefore monitoring requirements are lower than for the more biological monitoring parameters.

Table 4.6: The relative deviation (d') that can be detected with a probability of 80% with monthly sampling (12 per year) or biweekly sampling (26 samples per year). n is the number of stations or years used for calculating the indicator.

Site	Monthly sampling			Biweekly sampling		
	$n=1$	$n=2$	$n=3$	$n=1$	$n=2$	$n=3$
Oslo Fjord	0.18	0.13	0.10	0.12	0.09	0.07
Askö	0.04	0.03	0.02	0.02	0.02	0.01
Lahajalahti	0.06	0.04	0.03	0.04	0.03	0.02
Vanhankaupunginlahti	0.10	0.07	0.06	0.07	0.05	0.04
Moonsund	0.26	0.19	0.15	0.18	0.13	0.10
GoR Sandy	0.06	0.04	0.03	0.04	0.03	0.02
GoF Stony	0.09	0.07	0.05	0.06	0.05	0.04
GoR Trans	0.05	0.04	0.03	0.04	0.03	0.02
Curonian Northern Lagoon	0.24	0.17	0.14	0.16	0.11	0.09
Curonian Central lagoon	0.21	0.15	0.12	0.14	0.10	0.08
Limfjorden	0.29	0.20	0.17	0.20	0.14	0.11

4.2.4 Total phosphorus

Covariation analyses were carried out for 6 of the study areas resulting in 10 estimates of the residual variation, because the analyses also were conducted for specific sites within the chosen areas. The relative magnitude of the random variation (CV) varied from 6.4% at Askö to 56.0% in Limfjorden (Table 4.7). If a deviation from a boundary of 5% should be detected with a probability of 80% the required number of observations range from 12 to almost 1000. Given that the potential risk of overfitting data at sites with fewer data and thereby obtaining a too low estimate of the random variation, CV values are to be expected in the range 30–60% at non-analysed sites.

Table 4.7: Coefficients of variation for total phosphorus and calculated sample sizes for relative deviations from a boundary to be detected with a power of 80%.

Site	CV	d'=0.05	d'=0.10	d'=0.15	d'=0.20
Oslo Fjord	40.1%	462	116	51	29
Askö	6.4%	12	3	1	1
Lahajalahti	7.9%	18	5	2	1
Vanhankaupunginlahti	13.1%	49	12	5	3
GoR Sandy	14.6%	61	15	7	4
GoF Stony	15.6%	70	17	8	4
GoR Trans	9.3%	25	6	3	2
Curonian Northern Lagoon	54.2%	844	211	94	53
Curonian Central lagoon	54.6%	856	214	95	53
Limfjorden	56.0%	902	225	100	56

With monthly or biweekly sampling as recommended in Anonymous (2003) relative deviations from a boundary L on the order of 5–43% can be detected for monthly sampling and 3–29% for biweekly sampling if the indicator is calculated for a single station in a single year (Table 4.6). The relative deviation to be detected, d' , decreases if more years or stations are used for calculating the indicator. If 3 years with a single station or 3 stations in a single year is used then deviations of 3–25% can be detected with monthly sampling, and 2–17% can be detected with biweekly sampling.

These values could be compared to the deviation from the reference condition to the boundary between good and moderate ecological status, which is expected to be 25–50% (see Chapter 1). Total phosphorus, like total nitrogen, is one of the less variable monitoring parameters and therefore monitoring requirements are lower than for the more biological monitoring parameters, except for areas exposed to hypoxia and consequent releases from the sediments.

Table 4.8: The relative deviation (d') that can be detected with a probability of 80% with monthly sampling (12 per year) or biweekly sampling (26 samples per year). n is the number of stations or years used for calculating the indicator.

Site	Monthly sampling			Biweekly sampling		
	n=1	n=2	n=3	n=1	n=2	n=3
Oslo Fjord	0.13	0.09	0.07	0.09	0.06	0.05
Askö	0.15	0.10	0.08	0.10	0.07	0.06
Lahajalahti	0.26	0.19	0.15	0.18	0.13	0.10
Vanhankaupunginlahti	0.18	0.13	0.10	0.12	0.09	0.07
GoR Sandy	0.19	0.14	0.11	0.13	0.09	0.08
GoF Stony	0.27	0.19	0.15	0.18	0.13	0.10
GoR Trans	0.13	0.09	0.07	0.09	0.06	0.05
Curonian Northern Lagoon	0.15	0.10	0.08	0.10	0.07	0.06
Curonian Central lagoon	0.26	0.19	0.15	0.18	0.13	0.10
Limfjorden	0.18	0.13	0.10	0.12	0.09	0.07

4.3 Discussion and summary

Power analyses for calculating the required number of samples strongly rely on statistical assumptions, in some cases assumptions that are diffi-

cult to justify (Fox, 2001), particularly if historical data is scarce. Therefore, the sampling requirements (Table 3) should not be interpreted as exact numbers, but as an indication of monitoring efforts. Although the merits of power analyses for implementing the WFD were acknowledged at an early stage (Pollard and Huxham, 1998), this critical issue has been largely overlooked so far. Most efforts in the WFD implementation have been devoted to establishing reference conditions (e.g. Nijboer et al., 2004) and harmonising assessment systems (e.g. Moss 2003). Despite the large resources invested into WFD implementation so far, it is still questionable whether an operational WFD, including active management based on indicator assessment, is feasible at all and if so, what are the costs associated with making WFD operational.

The indicative monitoring frequencies (4 times per year for nutrients and 2 times per year for phytoplankton) stated in the text of the directive (Anonymous 2000) are obviously not providing sufficient precision for an operational implementation. This was acknowledged in Anonymous (2003) that recommended biweekly or monthly sampling for these variables. In this study the required number of samples is very variable depending on the given site in question. Moreover, the indicator boundary setting is also site-specific and no general guidelines can be given to tolerance or allowable deviation for classification. It can only be recommended to carry out site-specific analyses to obtain estimates of appropriate sample sizes.

However, it may be argued that data resulting from intensive monitoring is correlated in both time and space, and that this will require even more observations to obtain sufficient precision. However, the origin of such correlations, if present, is most likely due to the underlying biogeochemical and biological processes and not caused by the sampling and analytical procedures. To put it differently, residual correlation derives from the inadequacy of describing the variations in time and space with a simple statistical model. If the systematic variation can be more adequately described using more sophisticated models then the random variation is reduced, indicator precision improved and monitoring requirements reduced. It is also likely that sampling and analytical techniques can be improved to reduce the uncertainty.

References

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Sammenfatning

Formålet med det Europæiske Vandrammedirektiv (VRD) er at sikre en bæredygtig forvaltning af grundvand, ferskvand og marine farvande indenfor den Europæiske Union, således at god økologisk tilstand kan opnås senest i 2015 for alle vandområder. Vandområder skal vurderes i henhold til fem grupper (høj, god, moderat, ringe, og dårlig) ud fra den økologiske tilstand af en prioriteret liste for 1) biologiske elementer, 2) kemiske og fysisk-kemiske elementer, og 3) hydro-morfologiske elementer. De biologiske elementer indbefatter fytoplankton, andre akvatiske planter, bundfauna og fisk. Kemiske og fysisk-kemiske elementer indbefatter sigtddybde, salinitet, temperatur, næringssalte, ilt og specifikke forurenende stoffer. Hydromorfologiske elementer indbefatter dybdevariationer, sedimenter, bølger, tidevand og vandføringsmæssige karakteristika. Overvågningsprogrammer til at klassificere vandområder skal være operationelle i december 2006.

Overvågningsdata til beskrivelse af de biologiske og fysisk-kemiske elementer er behæftet med store usikkerheder. Konfidensgrænser til klassifikation skal beskrive usikkerheder som stammer fra prøveindsamling og -analyse, hvorfor det er vigtigt at kunne opdele den totale variation i indsamlings- og analyseusikkerhed og så alle andre kilder til variation. Den store variation i overvågningsdata skyldes ofte sæsonvariationer såvel som specifikke omstændigheder ved prøvetagninger, som kan karakteriseres ved f.eks. saltindhold eller vind. Ved at tage højde for disse variationer i beregningen af indikatorer forbedres præcisionen (den tilfældige variation reduceres) og indikatoren bliver mere generel (uafhængig af de specifikke prøvetagningsomstændigheder).

I nærværende rapport er 7 områder fra 4 nordiske lande og 3 baltiske lande blevet analyseret (Oslo fjorden, Askö, Laajalahti and Vanhankaupunginlahti bugt, Moonsund, Rigabugten, Curonian lagune og Limfjorden). Hovedvægten i analysen var indenfor det biologiske element fytoplankton biomasse, målt som klorofyl a, og de understøttende fysisk-kemiske elementer sigtddybde, total kvælstof og total fosfor. Statistiske modeller er blevet udviklet til at beskrive sæsonvariationen foruden en afhængighed af de specifikke prøvetagningsforhold for hvert af de enkelte områder. Den største effekt til at forbedre præcisionen og beregne uafhængige indikatorer opnåedes ved at inkludere en model for sæsonvariationer, men salinitet og vindforhold påvirkede også enkeltmålinger i væsentlig grad. Der skal dog også udvises forsigtighed ved anvendelse af statistiske modeller for at beskrive variationer i data, specielt når der kun er få observationer til rådighed, idet over-parameteriserede modeller resulterer i for små estimer af den tilfældige variation. Generelt set blev

den tilfældige variation reduceret omkring 20 % ved modellerne anvendt på de 7 områder, hvorimod de estimerede indikatorer kunne ændres med 10–20 % når der blev taget højde for variationer i prøvetagningsforholdene.

Hvis en beregnet indikator er afhængig af prøvetagningsforholdene kan dette give anledning til forkert klassifikation, hvorimod en dårlig præcision resulterer i manglende styrke til klassifikationen. Tre metoder er anvist til klassifikation af indikatorer hvor usikkerheden er taget i betragtning. Ved 'Fail-safe approach' kommer usikkerheden forurenerne til gode, hvorimod usikkerheden kommer miljøet til gode i 'Benefit-of-doubt approach'. I 'Face value approach' deles usikkerhed ligeligt mellem forurenere og miljø. Når usikkerheden på en indikator er stor kan der opnås meget forskellige klassifikationer afhængig af hvilken metode, som anvendes. De statistiske principper bagved klassifikationen af usikre indikatorer er beskrevet i denne rapport. Det anbefales at anvende et standard 95 % konfidensniveau.

Hvis størrelsen af den tilfældige variation er kendt, kan antallet af prøvetagninger bestemmes, hvis en tilladelig afvigelse fra grænsen mellem tilstandsklasser er specificeret således at data vil resultere i en korrekt klassifikation med mindst 80 % (styrken) når den sande middelværdi afviger mere end specificeret. Prøvetagningsomfanget vokser med kvadratet på den tilfældige variation. Dette understreger vigtigheden af at kunne beskrive systematiske variationer i overvågningsdata. For de 7 undersøgte områder var der store variationer i overvågningsbehovet (~10 til ~1000 prøver), som skyldtes store forskelle i størrelsen på den tilfældige variation. En ligeså vigtig parameter for at beregne antallet af prøvetagninger er den tilladelige afvigelse fra grænseværdier, hvor indikatoren skal klassificeres korrekt med en sandsynlighed på mindst 80 %. På nuværende tidspunkt er det vigtigt, at der udarbejdes fælles europæiske retningslinier for klassifikation ifm. vandrammedirektivet. Nærværende rapport beskriver det tekniske grundlag for at træffe sådanne beslutninger.

Appendices

A Model parameters for Laajalahti and Vanhankaupunginlahti example

Table A.1 Model parameters for Secchi depth including salinity in Laajalahti

Dependent	Parameter	Estimate	StdErr	tValue	Probt
Secchi	intercept	0.787	0.212	3.71	0.0003
Secchi	month4	0.085	0.085	1.00	0.3208
Secchi	month5	-0.231	0.067	-3.45	0.0008
Secchi	month6	-0.360	0.065	-5.56	< 0.0001
Secchi	month7	-0.424	0.066	-6.47	< 0.0001
Secchi	month8	-0.436	0.060	-7.31	< 0.0001
Secchi	month9	-0.377	0.068	-5.58	< 0.0001
Secchi	month10	-0.130	0.073	-1.77	0.0787
Secchi	month11	0.0	.	.	.
Secchi	Salinity	0.093	0.045	2.06	0.0411

Table A.2 Model parameters for logTP including salinity in Laajalahti

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logTP	intercept	1.690	0.083	20.40	< 0.0001
logTP	month1	-0.049	0.048	-1.02	0.3107
logTP	month2	0.018	0.052	0.34	0.7317
logTP	month3	0.003	0.050	0.06	0.9498
logTP	month4	0.010	0.049	0.21	0.8302
logTP	month5	0.154	0.045	3.42	0.0008
logTP	month6	0.226	0.045	5.01	< 0.0001
logTP	month7	0.286	0.045	6.29	< 0.0001
logTP	month8	0.323	0.044	7.33	< 0.0001
logTP	month9	0.276	0.046	6.01	< 0.0001
logTP	month10	0.175	0.047	3.74	0.0003
logTP	month11	0.044	0.047	0.93	0.3552
logTP	month12	0.0	.	.	.
logTP	Salinity	0.031	0.015	1.98	0.0498

Table A.3 Model parameters for logTN including salinity in Laajalahti

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logTN	intercept	3.240	0.075	42.98	< 0.0001
logTN	month1	0.151	0.043	3.47	0.0007
logTN	month2	0.211	0.048	4.43	< 0.0001
logTN	month3	0.164	0.046	3.59	0.0004
logTN	month4	-0.050	0.045	-1.11	0.2688
logTN	month5	-0.147	0.041	-3.58	0.0005
logTN	month6	-0.0978	0.041	-2.38	0.0187
logTN	month7	-0.046	0.041	-1.11	0.2709
logTN	month8	-0.030	0.040	-0.75	0.4572
logTN	month9	-0.029	0.042	-0.71	0.4793
logTN	month10	-0.078	0.043	-0.81	0.0720
logTN	month11	-0.056	0.043	1.29	0.1988
logTN	month12	0.0	.	.	.
logTN	Salinity	0.077	0.014	5.33	<0.0001

Table A.4 Model parameters for Secchi depth including the weekly water flow of the River Vantaa and logTP in Vanhankaupunginlahti

Dependent	Parameter	Estimate	StdErr	tValue	Probt
secchi	intercept	0.953	0.080	11.95	<0.0001
secchi	month4	0.015	0.057	0.27	0.7901
secchi	month5	0.015	0.049	-0.30	0.7607
secchi	month6	0.042	0.051	-0.82	0.4139
secchi	month7	0.030	0.051	-0.59	0.5566
secchi	month8	0.042	0.050	0.84	0.3998
secchi	month9	0.0215	0.053	0.41	0.6840
secchi	month10	0.0002	0.057	0.00	0.997
secchi	month11	0.0	.	.	.
secchi	water flow	-0.482	0.033	-14.33	< 0.0001

Table A.5 Model parameters for logTN including salinity in Vanhankaupunginlahti

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logTN	intercept	3.553	0.061	58.63	< 0.0001
logTN	month1	0.031	0.065	0.47	0.6395
logTN	month2	0.039	0.067	0.58	0.5611
logTN	month3	-0.113	0.068	-1.66	0.0976
logTN	month4	-0.181	0.064	-2.83	0.0051
logTN	month5	-0.305	0.060	-5.09	< 0.0001
logTN	month6	-0.313	0.061	-5.14	< 0.0001
logTN	month7	-0.2972	0.061	-4.89	< 0.0001
logTN	month8	-0.283	0.060	-4.73	< 0.0001
logTN	month9	-0.226	0.062	-3.68	0.0003
logTN	month10	-0.124	0.063	-1.95	0.052
logTN	month11	-0.038	0.064	-0.59	0.5581
logTN	month12	0.0	.	.	.
logTN	Salinity	-0.110	0.0079	-13.94	< 0.0001

Table A.6 Model parameters for logCHLa including salinity in Vanhankaupunginlahti

Dependent	Parameter	Estimate	StdErr	tValue	Probt
Intercept		0.353	0.133	2.66	0.0089
logCHL	month4	-0.282	0.128	-2.19	0.0306
logCHL	month5	0.383	0.105	3.66	0.0004
logCHL	month6	0.649	0.104	6.23	< 0.0001
logCHL	month7	0.431	0.102	4.22	< 0.0001
logCHL	month8	0.459	0.101	4.54	< 0.0001
logCHL	month9	0.234	0.103	2.27	0.0247
logCHL	month10	0.0	.	.	.
logCHL	Salinity	0.093	0.024	3.94	0.0001

B Model parameters for Gulf of Riga example

Table B.1 Model parameters for winter DIN

Survey	Slope	Std.Err	t	p
6	-4.93	5.55	-0.89	0.37
7	-2.69	5.62	-0.48	0.63
13	-12.54	4.87	-2.58	0.01
17	-4.63	34.17	-0.14	0.89
21	-13.54	8.07	-1.68	0.09
24	-21.95	13.73	-1.60	0.11
29	-25.26	2.38	-10.61	0.00
33	-22.59	4.74	-4.76	0.00
36	-21.50	2.79	-7.69	0.00
39	-14.15	1.99	-7.10	0.00
40	-10.88	2.68	-4.05	0.00
41	-18.38	15.43	-1.19	0.23
42	-8.73	1.50	-5.84	0.00
43	-4.32	1.59	-2.71	0.01
47	-18.24	1.67	-10.94	0.00
50	-5.43	1.01	-5.38	0.00
51	-9.90	4.27	-2.31	0.02
52	-7.57	1.53	-4.95	0.00
53	-20.33	1.12	-18.14	0.00
54	-13.53	1.73	-7.80	0.00
56	-20.40	2.17	-9.40	0.00
57	-16.82	1.41	-11.95	0.00
58	-19.57	1.19	-16.49	0.00
59	-16.05	0.95	-16.88	0.00
60	-13.56	1.27	-10.66	0.00
61	-12.78	1.41	-9.04	0.00
62	-12.27	5.77	-2.13	0.03
63	-13.70	0.85	-16.09	0.00
64	-23.43	2.42	-9.68	0.00
65	-22.48	3.08	-7.31	0.00
66	-9.86	1.59	-6.21	0.00
67	-16.24	1.51	-10.73	0.00
69	-19.60	1.58	-12.37	0.00
70	-21.17	0.74	-28.70	0.00
71	-18.44	3.65	-5.06	0.00
72	-27.29	1.27	-21.45	0.00
73	-18.74	1.40	-13.37	0.00
74	-14.42	0.97	-14.93	0.00
75	-13.88	4.32	-3.21	0.00
76	-18.95	3.53	-5.37	0.00
78	-15.79	3.07	-5.14	0.00
80	-19.15	1.37	-14.00	0.00

Table B.2 Model parameters for winter N_{tot}

Survey	Slope	Std.Err	t	p
33	-28.05	6.33	-4.43	0.00
36	-28.94	3.73	-7.77	0.00
39	-17.73	2.66	-6.68	0.00
41	-12.34	20.59	-0.60	0.55
42	-17.89	2.00	-8.96	0.00
43	-13.32	2.13	-6.27	0.00
44	-31.62	7.38	-4.29	0.00
47	-27.87	2.26	-12.31	0.00
50	-21.27	1.35	-15.81	0.00
51	-11.36	5.91	-1.92	0.06
55	-16.92	118.10	-0.14	0.89
56	-25.37	2.89	-8.77	0.00
57	-21.22	1.88	-11.31	0.00
58	-24.03	1.58	-15.18	0.00
59	-20.93	1.19	-17.54	0.00
60	-18.17	1.70	-10.71	0.00
61	-20.74	1.88	-11.00	0.00
62	-15.12	6.25	-2.42	0.02
63	-16.39	1.14	-14.44	0.00
64	-25.72	3.23	-7.97	0.00
65	-26.24	4.10	-6.40	0.00
66	-18.73	2.12	-8.85	0.00
67	-20.14	2.02	-9.98	0.00
69	-24.85	2.11	-11.75	0.00
70	-25.52	0.98	-25.94	0.00
71	-25.09	4.86	-5.16	0.00
72	-34.02	1.70	-20.05	0.00
73	-25.58	1.87	-13.68	0.00
74	-18.82	1.29	-14.60	0.00
75	-19.36	5.76	-3.36	0.00
76	-24.91	4.71	-5.29	0.00
78	-21.86	4.09	-5.34	0.00
80	-25.52	1.82	-13.99	0.00

Table B.3 Model parameters for winter DIP

Survey	Slope	Std.Err	t	p
1	-1.02	0.33	-3.10	0.00
2	4.30	1.86	2.32	0.02
3	0.00	0.34	0.00	1.00
6	-0.03	0.14	-0.22	0.83
7	-0.06	0.14	-0.44	0.66
11	-2.98	1.16	-2.58	0.01
13	-0.30	0.12	-2.50	0.01
17	-0.20	0.10	-2.05	0.04
20	-0.20	0.04	-5.05	0.00
21	0.11	0.20	0.55	0.58
24	-0.14	0.34	-0.43	0.67
25	-0.33	0.05	-7.07	0.00
29	-0.30	0.06	-5.08	0.00
33	-0.34	0.12	-2.90	0.00
36	-0.22	0.07	-3.12	0.00
39	-0.34	0.05	-6.95	0.00
40	-0.25	0.07	-3.70	0.00
41	-0.37	0.38	-0.97	0.33
42	-0.27	0.04	-7.37	0.00
43	-0.13	0.04	-3.23	0.00
44	-0.34	0.14	-2.51	0.01
47	-0.04	0.04	-0.94	0.35
50	-0.31	0.02	-12.65	0.00
51	-0.19	0.11	-1.76	0.08
52	-0.13	0.04	-3.34	0.00
53	-0.13	0.03	-4.76	0.00
54	-0.02	0.04	-0.49	0.62
55	5.45	2.18	2.50	0.01
56	-0.18	0.05	-3.35	0.00
57	-0.10	0.03	-2.78	0.01
58	-0.12	0.03	-4.20	0.00
59	-0.12	0.02	-5.18	0.00
60	-0.10	0.03	-3.11	0.00
61	-0.21	0.03	-6.04	0.00
62	-0.12	0.12	-1.08	0.28
63	-0.18	0.02	-8.77	0.00
64	-0.15	0.06	-2.56	0.01
65	-0.10	0.08	-1.36	0.17
66	-0.18	0.04	-4.71	0.00
67	-0.19	0.04	-4.98	0.00
69	-0.14	0.04	-3.52	0.00
70	-0.18	0.02	-10.08	0.00
71	-0.23	0.09	-2.51	0.01
72	-0.16	0.03	-5.17	0.00
73	-0.06	0.03	-1.84	0.07
74	-0.01	0.02	-0.29	0.77
75	-0.15	0.11	-1.41	0.16
76	-0.24	0.09	-2.72	0.01
78	-0.20	0.08	-2.66	0.01
80	-0.16	0.03	-4.88	0.00

Table B.4 Model parameters for winter P_{tot}

Survey	Slope	Std.Err	t	p
1	-0.89	0.54	-1.66	0.10
2	5.31	3.03	1.75	0.08
3	0.03	0.56	0.06	0.95
6	0.15	0.22	0.67	0.51
7	-0.43	0.23	-1.89	0.06
11	-2.84	1.89	-1.50	0.13
13	-0.44	0.20	-2.25	0.03
17	-0.35	0.16	-2.14	0.03
20	-0.21	0.06	-3.35	0.00
21	-0.04	0.33	-0.11	0.91
24	0.90	0.55	1.62	0.11
25	-0.33	0.08	-4.27	0.00
29	-0.34	0.09	-3.59	0.00
33	-0.37	0.19	-1.95	0.05
36	-0.25	0.11	-2.24	0.03
39	-0.59	0.08	-7.37	0.00
40	-0.92	0.11	-8.56	0.00
41	-0.21	0.62	-0.33	0.74
42	-0.34	0.06	-5.59	0.00
43	-0.23	0.06	-3.55	0.00
44	-0.39	0.22	-1.74	0.08
47	-0.04	0.07	-0.67	0.50
50	-0.39	0.04	-9.64	0.00
51	0.03	0.18	0.16	0.87
52	-0.04	0.06	-0.60	0.55
53	-0.16	0.05	-3.60	0.00
54	-0.08	0.09	-0.92	0.36
55	11.20	3.56	3.14	0.00
56	-0.31	0.09	-3.58	0.00
57	-0.11	0.06	-2.00	0.05
58	-0.17	0.05	-3.51	0.00
59	-0.17	0.04	-4.41	0.00
60	-0.16	0.05	-3.14	0.00
61	-0.23	0.06	-4.04	0.00
62	-0.11	0.19	-0.58	0.56
63	-0.24	0.03	-6.97	0.00
64	-0.17	0.10	-1.79	0.07
65	-0.18	0.12	-1.43	0.16
66	-0.15	0.06	-2.37	0.02
67	-0.20	0.06	-3.33	0.00
69	-0.19	0.06	-2.93	0.00
70	-0.31	0.03	-10.49	0.00
71	-0.26	0.15	-1.78	0.08
72	-0.33	0.05	-6.43	0.00
73	-0.17	0.06	-3.01	0.00
74	-0.09	0.04	-2.43	0.02
75	-0.03	0.17	-0.18	0.86
76	-0.33	0.14	-2.29	0.02
78	-0.26	0.12	-2.08	0.04
80	-0.27	0.06	-4.88	0.00

Table B.5 Summer chlorophyll a model parameters

	Effect	Parameter	Std.Err	t	p
Intercept	0	1.796	0.151	11.93	0.000
YEAR	1996	-0.220	0.035	-6.31	0.000
YEAR	1997	-0.312	0.029	-10.69	0.000
YEAR	1998	0.076	0.033	2.29	0.022
YEAR	1999	-0.070	0.028	-2.52	0.012
YEAR	2000	0.195	0.029	6.77	0.000
YEAR	2001	0.148	0.028	5.35	0.000
YEAR	2002	0.040	0.027	1.49	0.136
MONTH	6	0.124	0.021	5.94	0.000
MONTH	7	-0.011	0.016	-0.66	0.508
WINDSPCL	low	0.048	0.016	2.96	0.003
WINDSPCL	medium	-0.028	0.014	-1.94	0.053
AIRTEMP		-0.014	0.004	-3.22	0.001
SALINITY		-0.161	0.026	-6.15	0.000

C Model parameters for Curonian Lagoon example

Table C.1 Model parameters for TN for the northern part of the Curonian Lagoon

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logTN	intercept	1605,774	44,3362	36,21808	0,000000
logTN	month1	175,779	141,4897	1,24234	0,215744
logTN	month2	306,997	141,8852	2,16370	0,031820
logTN	month3	286,302	122,2462	2,34201	0,020286
logTN	month4	60,726	122,8508	0,49431	0,621699
logTN	month5	-189,389	99,5009	-1,90339	0,058604
logTN	month6	-389,025	104,1176	-3,73640	0,000251
logTN	month7	-206,115	106,1578	-1,94159	0,053765
logTN	month8	-17,211	100,3625	-0,17149	0,864033
logTN	month9	136,876	113,9423	1,20127	0,231242
logTN	month10	11,969	104,0169	0,11507	0,908520
logTN	month11	-223,014	125,2258	-1,78090	0,076635
logTN	month12	0.0	.	.	.
logTN	Salinity	-96,629	18,2367	-5,29860	0,000000

Table C.2 Model parameters for TN for the central part of the Curonian Lagoon

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logTN	intercept	1600,142	44,6280	35,85510	0,000000
logTN	month1	578,191	180,2042	3,20853	0,001761
logTN	month2	569,858	167,6872	3,39834	0,000953
logTN	month3	309,858	167,6872	1,84783	0,067389
logTN	month4	-11,253	149,3751	-0,07534	0,940088
logTN	month5	-481,571	122,7002	-3,92478	0,000154
logTN	month6	-361,809	131,2730	-2,75616	0,006877
logTN	month7	78,191	131,2730	0,59564	0,552676
logTN	month8	-85,428	122,7002	-0,69623	0,487792
logTN	month9	-306,142	142,4107	-2,14971	0,033831
logTN	month10	-258,324	136,4483	-1,89320	0,061033
logTN	month11	-67,142	142,4107	-0,47147	0,638266
logTN	month12	0.0	.	.	.

Table C.3 Model parameters for TP for the northern part of the Curonian Lagoon

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logTP	intercept	99,0359	3,38368	29,26865	0,000000
logTP	month1	-0,1220	10,54450	-0,01157	0,990773
logTP	month2	15,3088	10,10624	1,51479	0,130828
logTP	month3	-13,5355	10,05216	-1,34653	0,179101
logTP	month4	-29,1178	8,72733	-3,33639	0,000950
logTP	month5	-38,0449	7,74286	-4,91355	0,000001
logTP	month6	-12,4909	7,72275	-1,61742	0,106789
logTP	month7	7,5040	7,81099	0,96070	0,337439
logTP	month8	32,6914	7,60899	4,29642	0,000023
logTP	month9	12,8980	8,32437	1,54943	0,122283
logTP	month10	7,1846	8,73041	0,82294	0,411163
logTP	month11	-7,5233	9,85831	-0,76314	0,445952
logTP	month12	0.0	.	.	.
logTP	Salinity	-7,7527	1,23694	-6,26765	0,000000

Table C.4 Model parameters for TP for the central part of the Curonian Lagoon

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logTP	intercept	136,0428	4,82309	28,20660	0,000000
logTP	month1	-30,7428	22,28122	-1,37976	0,168729
logTP	month2	-31,8762	20,43496	-1,55988	0,119886
logTP	month3	-20,1762	18,40441	-1,09627	0,273878
logTP	month4	-17,0028	14,57869	-1,16628	0,244466
logTP	month5	-26,5984	12,43800	-2,13848	0,033319
logTP	month6	5,1516	12,43800	0,41418	0,679048
logTP	month7	58,2143	12,58807	4,62456	0,000006
logTP	month8	70,6869	12,29437	5,74954	0,000000
logTP	month9	52,3511	12,90942	4,05526	0,000065
logTP	month10	8,1424	14,08964	0,57790	0,563785
logTP	month11	-39,3928	16,12009	-2,44371	0,015137
logTP	month12	0.0	.	.	.

Table C.5 Model parameters for SD for the northern part of the Curonian Lagoon

Dependent	Parameter	Estimate	StdErr	tValue	Probt
secchi	intercept	0,749119	0,032983	22,71241	0,000000
secchi	month1	0,164329	0,194352	0,84552	0,398564
secchi	month2	-0,028488	0,115046	-0,24762	0,804614
secchi	month3	-0,045474	0,109412	-0,41562	0,678016
secchi	month4	0,103248	0,070269	1,46933	0,142898
secchi	month5	0,091969	0,062992	1,46000	0,145444
secchi	month6	-0,108486	0,063042	-1,72086	0,086413
secchi	month7	-0,119483	0,062973	-1,89735	0,058840
secchi	month8	-0,166993	0,062164	-2,68636	0,007668
secchi	month9	-0,154218	0,065543	-2,35291	0,019340
secchi	month10	-0,050241	0,070618	-0,71144	0,477423
secchi	month11	0,254938	0,080896	3,15143	0,001806
secchi	month12	0.0	.	.	.
secchi	Salinity	0,103318	0,010152	10,17751	0,000000

Table C.6 Model parameters for SD for the central part of the Curonian Lagoon

Dependent	Parameter	Estimate	StdErr	tValue	Probt
secchi	intercept	0,857154	0,044004	19,47913	0,000000
secchi	month1	-0,163602	0,130116	-1,25735	0,209670
secchi	month2	0,027095	0,118563	0,22853	0,819404
secchi	month3	0,021227	0,093756	0,22640	0,821053
secchi	month4	0,168158	0,063364	2,65383	0,008412
secchi	month5	0,081452	0,057717	1,41125	0,159278
secchi	month6	0,010560	0,057680	0,18307	0,854873
secchi	month7	-0,116561	0,058026	-2,00876	0,045519
secchi	month8	-0,138618	0,056842	-2,43864	0,015362
secchi	month9	-0,065877	0,058746	-1,12138	0,263084
secchi	month10	0,046951	0,065087	0,72137	0,471284
secchi	month11	0,204594	0,074118	2,76040	0,006153
secchi	month12	0.0	.	.	.
secchi	Wind velocity	-0,029005	0,007403	-3,91795	0,000112

Table C.7 Model parameters for CHL for the northern part of the Curonian Lagoon

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logCHL	intercept	42,4277	8,29570	5,11443	0,000001
logCHL	month1	-36,9610	32,19978	-1,14787	0,252355
logCHL	month2	-30,0154	29,97564	-1,00133	0,317844
logCHL	month3	-23,2759	29,97564	-0,77649	0,438348
logCHL	month4	-11,4254	29,97564	-0,38116	0,703479
logCHL	month5	-7,5761	21,99270	-0,34448	0,730834
logCHL	month6	-11,1926	25,48770	-0,43914	0,661023
logCHL	month7	18,5755	25,48770	0,72880	0,466950
logCHL	month8	21,7396	21,99270	0,98849	0,324071
logCHL	month9	24,8762	28,19263	0,88237	0,378607
logCHL	month10	72,2524	24,42995	2,95753	0,003463
logCHL	month11	7,9423	28,19263	0,28171	0,778446
logCHL	month12	0.0	.	.	.

Table C.8 Model parameters for CHL for the central part of the Curonian Lagoon

Dependent	Parameter	Estimate	StdErr	tValue	Probt
logCHL	intercept	83,0445	13,49923	6,15180	0,000000
logCHL	month1	-41,3063	34,01561	-1,21433	0,226202
logCHL	month2	-18,4018	30,38265	-0,60567	0,545493
logCHL	month3	-35,4502	25,59500	-1,38504	0,167744
logCHL	month4	-25,5830	23,21745	-1,10189	0,271974
logCHL	month5	-15,0749	17,80199	-0,84681	0,398219
logCHL	month6	-4,0063	19,55071	-0,20492	0,837866
logCHL	month7	112,0364	19,78618	5,66235	0,000000
logCHL	month8	48,0519	17,47953	2,74904	0,006583
logCHL	month9	39,0366	20,49632	1,90457	0,058422
logCHL	month10	-2,1722	19,56717	-0,11101	0,911728
logCHL	month11	-25,7461	21,57116	-1,19354	0,234219
logCHL	month12	0.0	.	.	.
logCHL	Wind velocity	-7,4542	2,38711	-3,12270	0,002087

D Model parameters for Limfjorden example

Table D.1 Model parameters for TN

Dependent	Parameter	Estimate	StdErr	tValue	Probt
TN	Intercept	161.24	3.44	46.85	<0.01
TN	month 1	9.82	2.33	4.22	<0.01
TN	month 2	23.62	2.20	10.76	<0.01
TN	month 3	13.49	2.04	6.61	<0.01
TN	month 4	2.09	1.99	1.05	0.29
TN	month 5	-12.91	2.05	-6.30	<0.01
TN	month 6	-23.89	2.07	-11.55	<0.01
TN	month 7	-22.52	2.03	-11.09	<0.01
TN	month 8	-18.74	2.05	-9.12	<0.01
TN	month 9	-18.74	2.05	-9.15	<0.01
TN	month 10	-18.03	2.11	-8.55	<0.01
TN	month 11	-7.96	2.18	-3.65	<0.01
TN	month 12	0.00			
TN	Salinity	-3.48	0.12	-30.06	<0.01

Table D.2 Model parameters for TP

Subgroup	Dependent	Parameter	Estimate	StdErr	tValue	Probt
Rest	TP	Intercept	1.16	0.23	5.07	<0.01
Rest	TP	Salinity*month 1	0.02	0.01	1.97	0.05
Rest	TP	Salinity*month 2	0.02	0.01	2.56	0.01
Rest	TP	Salinity*month 3	-0.01	0.01	-1.05	0.29
Rest	TP	Salinity*month 4	-0.02	0.01	-2.55	0.01
Rest	TP	Salinity*month 5	-0.03	0.01	-3.18	<0.01
Rest	TP	Salinity*month 6	-0.02	0.01	-2.19	0.03
Rest	TP	Salinity*month 7	-0.02	0.01	-1.77	0.08
Rest	TP	Salinity*month 8	0.00	0.01	0.44	0.66
Rest	TP	Salinity*month 9	0.01	0.01	1.72	0.09
Rest	TP	Salinity*month 10	0.01	0.01	1.47	0.14
Rest	TP	Salinity*month 11	0.01	0.01	1.75	0.08
Rest	TP	Salinity*month 12	0.02	0.01	2.51	0.01
Rest	TP	Temperature*Station (Kås)	0.05	0.01	6.06	<0.01
Rest	TP	Temperature*Station (Løgstør)	0.06	0.01	7.79	<0.01
Rest	TP	Temperature*Station (Nibe)	0.08	0.01	9.71	<0.01
Rest	TP	Temperature*Station (Nissum)	0.03	0.01	2.80	0.01
Rest	TP	Temperature*Station (Thisted)	0.06	0.01	7.12	<0.01
Skive-Lovns	TP	Intercept	3.13	0.68	4.59	<0.01
Skive-Lovns	TP	Salinity*month 1	-0.08	0.03	-2.77	0.01
Skive-Lovns	TP	Salinity*month 2	-0.09	0.03	-3.06	<0.01
Skive-Lovns	TP	Salinity*month 3	-0.13	0.03	-4.33	<0.01
Skive-Lovns	TP	Salinity*month 4	-0.18	0.03	-5.94	<0.01
Skive-Lovns	TP	Salinity*month 5	-0.24	0.03	-7.83	<0.01
Skive-Lovns	TP	Salinity*month 6	-0.24	0.03	-7.73	<0.01
Skive-Lovns	TP	Salinity*month 7	-0.17	0.03	-5.50	<0.01
Skive-Lovns	TP	Salinity*month 8	-0.08	0.03	-2.71	0.01
Skive-Lovns	TP	Salinity*month 9	-0.07	0.03	-2.56	0.01
Skive-Lovns	TP	Salinity*month 10	-0.11	0.03	-4.05	<0.01
Skive-Lovns	TP	Salinity*month 11	-0.11	0.03	-3.87	<0.01
Skive-Lovns	TP	Salinity*month 12	-0.09	0.03	-3.02	<0.01
Skive-Lovns	TP	Temperature*Station (Lovns)	0.25	0.03	9.62	<0.01
Skive-Lovns	TP	Temperature*Station (Skive)	0.30	0.03	10.91	<0.01

Table D.3 Model parameters for ln(CHL)

Dependent	Parameter	Estimate	StdErr	tValue	Probt
ln_chl	Intercept	2.55	0.13	19.01	0.00
ln_chl	month 1	-0.08	0.09	-0.86	0.39
ln_chl	month 2	0.45	0.08	5.34	0.00
ln_chl	month 3	1.25	0.08	15.92	0.00
ln_chl	month 4	0.85	0.08	11.17	0.00
ln_chl	month 5	1.11	0.08	13.98	0.00
ln_chl	month 6	1.36	0.08	17.11	0.00
ln_chl	month 7	1.22	0.08	15.67	0.00
ln_chl	month 8	1.44	0.08	18.18	0.00
ln_chl	month 9	1.39	0.08	17.69	0.00
ln_chl	month 10	1.08	0.08	13.34	0.00
ln_chl	month 11	0.64	0.08	7.70	0.00
ln_chl	month 12	0.00			
ln_chl	Salinity	-0.07	0.00	-15.80	0.00

Table D.4 Model parameters for SD

Dependent	Parameter	Estimate	StdErr	tValue	Probt
Sd	Intercept	6.36	0.14	46.50	0.00
Sd	ln_chl*Gruppe Kås	-0.42	0.08	-5.38	0.00
Sd	ln_chl*Gruppe Lovns	-1.11	0.06	-19.42	0.00
Sd	ln_chl*Gruppe Løgstør	-1.04	0.06	-17.00	0.00
Sd	ln_chl*Gruppe Nibe	-1.13	0.08	-14.79	0.00
Sd	ln_chl*Gruppe Nissum	-0.40	0.07	-5.78	0.00
Sd	ln_chl*Gruppe Skive	-1.01	0.05	-21.27	0.00
Sd	ln_chl*Gruppe Thisted	-1.49	0.07	-22.86	0.00
Sd	wind*Gruppe Kås	-0.58	0.04	-15.71	0.00
Sd	wind*Gruppe Lovns	-0.20	0.04	-5.43	0.00
Sd	wind*Gruppe Løgstør	-0.12	0.04	-3.30	0.00
Sd	wind*Gruppe Nibe	-0.27	0.04	-7.37	0.00
Sd	wind*Gruppe Nissum	-0.57	0.04	-16.09	0.00
Sd	wind*Gruppe Skive	-0.27	0.03	-8.20	0.00
Sd	wind*Gruppe Thisted	0.28	0.04	7.77	0.00