# Mechanisms Controlling Shifts and Trends in Water Quality in the Baltic Sea Drainage Basin

Photo: Thomas Jarnetun/Azote

Rémon Saaltink
r.m.saaltink@students.uu.nl
Master thesis, juni 2013

MSc Thesis for Sustainable Development
Track: Global Change and Ecosystems (GCE)
Department of Geosciences, Utrecht University

Supervisors:
Dr. Ir. Ype van der Velde
Dr. Stefan Dekker

**Acknowledgements**

From Utrecht University, I would like to thank my supervisors Dr. Ir. Ype van der Velde and Dr. Stefan Dekker for their support, feedback, advice and guidance throughout the research. Especially Ype's help in R was invaluable.

From Stockholm University, I would like to thank Dr. Steve Lyon and Dr. Helen Dahlke for their support and advice during my stay in Stockholm. I also would like to thank Dr. Erik Smedberg, for providing me with land-use data. And last, but certainly not least, I would like to thank Norris Lam and Ylva Sjöberg, for helping me getting around at the university.

**Summary**

In the past decades, several shifts and trends in water quality were observed in the Baltic Sea which caused eutrophication of Baltic Sea water. Water quality of the Baltic Sea is dependent on the water quality of the catchments in the drainage basin as the Baltic Sea has little water exchange with the North Sea. Therefore, it is important to understand and identify mechanisms that control the water quality in the catchments surrounding the Baltic Sea, known as the Baltic Sea Drainage Basin (BSDB). The aim of this research is to quantify shifts and trends in water quality in terms of nitrogen and phosphorus in the BSDB and relate these shifts and trends to environmental, climatic and anthropogenic controls. To achieve this goal, a nutrient dataset of 117 rivers flowing into the Baltic Sea was combined with a land-use dataset and a dataset containing monthly data of temperature and precipitation. A Mann-Kendall trend test, shift-point analysis and robust factor analysis were applied to reveal and extract patterns of trends and shifts as well as the most important relationships among the variables investigated in this study.

It was found that temperature increased most at the coast, probably due to warming of Baltic Sea water and reduced sea ice cover during winter. Patterns of shifts in temperature point to influence of the North Atlantic Oscillation which also caused shifts in precipitation. Both temperature and precipitation influence run-off. Increased temperature enhances evaporation thereby decreasing the flow, while increased precipitation results in more run-off thereby increasing the flow. A change in flow was observed with positive trends in the north to negative trends in the south. An east-west gradient was observed for the nitrogen and phosphorus variables. Negative trends for dissolved inorganic nitrogen (DIN) and total nitrogen (TN) were most pronounced in eastern catchments. The opposite is true for dissolved inorganic phosphorus (DIP) and total phosphorus (TP), where most of the positive trends are found in eastern catchments. The reason for this difference is explained by the different controls for nitrogen and phosphorus in the BSDB. Changes in nitrogen are mainly controlled by land-use changes or changes in agricultural practices while changes in phosphorus are mainly controlled by societal changes subsequently leading to better technologies in reducing phosphorus from point sources. The results presented in this study indicate that the controls for changes in nitrogen and phosphorus are not the same. Therefore, improving water quality in the catchments requires different approaches. Because people in the BSDB rely on many ecosystem services that are vulnerable to eutrophication, it is important to further improve the water quality in the catchments draining into the Baltic Sea. This is necessary to secure and sustain ecosystem services in the future.

**Table of contents**

**Abbreviations and terminology**

| | |
|---|---|
| ARMA | Auto-Regressive-Moving-Average |
| BNI | Baltic Nest Institute |
| BSDB | Baltic Sea Drainage Basin |
| DIN | Dissolved Inorganic Nitrogen |
| DIP | Dissolved Inorganic Phosphorus |
| FAO | the Food and Agriculture Organization |
| HELCOM | Helsinki Commission |
| JCP | Baltic Sea Joint Comprehensive Environmental Action Plan |
| KNMI | the Royal Netherlands Meteorological Institute |
| MA | Monthly Average |
| N | Nitrogen |
| NAO | North Atlantic Oscillation |
| P | Phosphorus |
| SST | Sea Surface Temperature |
| TN | Total Nitrogen |
| TP | Total Phosphorus |
| YA | Yearly Average |
| YAA | Yearly seasonal Average of the snow Accumulation season |
| YAM | Yearly seasonal Average of the snow Melt season |

# Chapter 1. Introduction

## 1.1. Problem definition

In pre-industrial conditions 100-years ago, the Baltic Sea was an oligotrophic system. This changed when in 1920 the population started to grow rapidly and increased their agricultural activities (Schernewski & Neumann 2005, Savchuk et al., 2008). Later, around 1960, migration from rural to urban areas put even more stress on the environment (Thorborg, 2012). In the past decades, several shifts and trends in water quality were observed in the Baltic Sea that can be related to eutrophication. Problems include stagnation events that resulted in anoxic bottom waters, the spreading of dead bottom zones and increased frequency and intensity of algal blooms (Boesch et al., 2006; Österblom et al., 2007; Boesch et al., 2008; Pawlak et al., 2009; Matthäus and Schinke, 1999; Voss et al., 2011; Nausch et al., 1999; Wulff et al., 2001; Vahtera et al., 2007; Diaz & Rosenberg 2008; Conley et al., 2009). Of particular concern are blooms of toxic dinoflagellates and raphidophytes, which cause fish mortalities in the wild and aquaculture (Boesch et al., 2006). More of these events are likely to occur in the future as the majority of future projections point to increased nitrogen (N) and phosphorus (P) loads coming into the Baltic Sea in the next 100 years (Graham and Bergström, 2001; Reckermann, et al., 2011; Hägg et al., submitted).

It is essential to know what caused these shifts and changes in water quality in order to develop workable strategies that can prevent these shifts and changes in water quality that are predicted to occur in the future. This is important because the inhabitants of the BSDB depend on many ecosystem services. A change in water quality can alter ecosystems in this area in such a way that these services are halted. This poses both health- and economic threats to people living in the BSDB.

## 1.2. Literature review

Monitoring the water quality of the catchments surrounding the Baltic Sea is important as these catchments have a remarkable influence on the water quality of the Baltic Sea. This is because the Baltic Sea has little water exchange with the North Sea, and as a result is more susceptible to anthropogenic impact compared to other, more open, seas (Pawlak et al., 2009; Pastuzak and Igras, 2012a). Therefore, it is important to understand and identify mechanisms that control the water quality in the catchments surrounding the Baltic Sea, known as the Baltic Sea Drainage Basin (BSDB).

Inhabitants rely on the ecosystem services of the BSDB like food, wood, paper, fibers, seafood, $CO_2$ assimilation, and partial N and P retention. This demand results in an ecological footprint which corresponds to an area as large as 8.5–9.5 times the BSDB (Jansson et al., 1999). This pressure poses threats to the health of ecosystems. Today, eutrophication is the most severe threat to the Baltic Sea ecosystem (Boesch et al. 2006; Boesch et al., 2008; Pawlak et al. 2009).

Investigating possible controls on the water quality of the BSDB is not straightforward as catchments in the BSDB vary in their climatic, oceanographic and hydrologic characteristics (Graham and Bergström, 2001). Moreover, catchments also vary in their anthropogenic characteristics such as demography, economy, technology and lifestyle (Thorborg, 2012). Changes in one or more of these characteristics can lead to shifts and trends in the water quality of the BSDB catchments which in turn will affect the water quality of the Baltic Sea. Mechanisms behind these changes can be summarized in environmental, climatic and anthropogenic controls.

Land-use changes affect the hydrological cycle by altering processes like infiltration, groundwater recharge, base flow and run-off in catchments (Lin et al., 2007; Todd et al., 2007). According to Van der Velde et al. (2013), conversion of wetlands into forests or agriculture has a big impact on the terrestrial water balance, which in turn can cause changes in flow regimes. In the BSDB, wetlands are especially important as they can maintain high discharges in dry periods of the year (Lyon et al., 2012; Van der Velde et al., 2013). This confirms that wetlands contribute to the resilience of the BSDB to changes in flow regimes caused by climate change. Furthermore, wetlands act as a nutrient sink preventing N and P to be released to the rivers (Richardson et al., 1997). Expansion of agricultural area at the expense of wetlands during the 20$^{th}$ century in the BSDB caused a decrease in run-off from the catchments through enhanced evapotranspiration rates (Van der Velde et al., 2013). In contrast, this expansion caused an increase in the amount of nutrients transported to the Baltic Sea (Temnerud et al., 2007; Voss et al., 2011). Furthermore, Krause et al. (2008) showed that land-use changes may have a big impact on nitrate retention, especially radical changes from intensive agriculture to extensive pasture lead to more N retention. Conversion of wetlands or forest to urban, artificial, areas also have a big impact on the water quality and hydrology of catchments (Todd et al., 2007; Cuo et al., 2009). It was found that reduced forest cover due to logging generally results in decreased evapotranspiration, increased snow accumulation, increased severity of rain-on-snow events, and increased stream flow during fall, winter and spring (Cuo et al., 2009). Moreover, conversion of coniferous forest to agricultural land had a bigger impact on the hydrology than deciduous forest, especially in

winter (Cuo et al., 2009). These studies confirm that land-use changes can contribute to changes in water quality and quantity in the BSDB.

The cold, northern, regions are more sensitive to climate change compared to the southern regions (Lyon et al., 2010; Teutschbein and Seibert, 2010). Shifts and trends in water quality and quantity due to climate change will be more pronounced in the northern catchments than in the southern catchments. Climate change in terms of trends in temperature and precipitation causes changes in river flow regimes, which in turn affect hydrology and water quality. According to Wilson and Lawrence (2010), a trend in temperature may cause long-term changes in the seasonal distribution of flow and in the magnitude and frequency of floods and droughts in Scandinavia. In their study, they found that the observed trends in streamflow can be explained by positive trends in temperature rather than positive trends in precipitation, likely because of an increase in the length of the snowmelt season. The same conclusion from model results were reported by Moore et al. (2008) who found that climate change projections for the rivers of the Galten basin predict changes in the timing of discharge and nutrient delivery due to increased winter precipitation and earlier snowmelt. These changes in the timing of nutrient delivery due to changes in flow regimes have implications for the water quality in the BSDB. Arheimer and Lidén (2000) showed that N and P concentrations were elevated during flow peaks at low-flow conditions as accumulated N and P may be flushed out during the first high-flow event. Moreover, Wright (1998) reported that an increase in temperature resulted in an increase in decomposition leading to enhanced amounts of N in a catchment area in Norway. The same observations were reported for P (Bowes et al., 2009). Therefore, an increasing trend in temperature can result in an increasing trend in N- and P-loads. Moreover, Meier et al. (2012) showed in a model that an increase in precipitation is important in the catchments of the Baltic Sea and will result in higher discharges.

Oceanographic changes, like warming of the Baltic Sea water, will also influence climate conditions in the BSDB catchments, especially for the catchments located at the coast. Several studies reported a warming of Baltic Sea water in the past (Feistel et al., 2004; Boesch et al., 2006; Alheit et al., 2012) and in the future (Meier et al., 2011). This warming will not only induce changes in sea water-salinity, redox conditions or ventilation rate of bottom water (Nausch et al., 2003) but will also result in reduced sea ice cover in the northern parts of the Baltic Sea (Neumann, 2010) and enhanced decomposition rates in Baltic Sea water which increase nutrient concentrations (Boesch et al., 2006). Warming of Baltic Sea water will in turn result in temperature increases in the northern catchments during winter which affect precipitation and flow patterns.

A human induced increase of N and P input into catchments has implications for the water quality and ecosystem services in the BSDB. According to Galloway et al. (2003), streams and rivers have a very high transfer rate for nitrogen, which has potential negative effects on biodiversity and ecological structure downstream in lakes and seas. The same observations were reported for phosphorus (Boesch et al., 2006; Boesch et al., 2008; Pastuzak and Igras, 2012b). Growing agroecosystems are the main cause for enhanced loads of N and P in the environment (Galloway et al., 2003; Sellner et al., 2003). According to the Food and Agriculture Organization (FAO), the use of the three main nutrients (N, $P_2O_5$, $K_2O$) will increase from 2012 to 2016 by 0.3% in western Europe (including Sweden and Finland), 3.8% in eastern Europe (including Belarus, Estonia, Latvia and Lithuania) and 1.8% in central Europe (including Poland). Hence, changes in the use of nutrients are not equally distributed in the BSDB. The Helsinki Commission (HELCOM) reports that at least 45% of N and P in the riverine outflow have their origin in diffuse sources (HELCOM, 2011). From these diffuse sources, agriculture contributed to 70 - 90% of the riverine N-load and 60% - 80% of the riverine P-load (HELCOM, 2011). Point sources like wastewater from industries form also a significant source of riverine N- and P-loads although this source is highly reduced through improved wastewater treatment in most countries. In the past decades, the population in the BSDB experienced almost no growth so an increase in N and P is not the result of population growth (Thorborg, 2012). However, it was found that population density together with river discharge is a good proxy for the flux of total nitrogen (TN) and total phosphorus (TP) from catchments (Smith et al., 2003; Smith et al., 2005; Hägg et al., submitted). Therefore, migration out of rural areas to the urban areas had an effect on water quality. Another important anthropogenic factor influencing the water quality is the changing lifestyle of society (e.g. consumption behavior). It was found by Hägg et al. (submitted) that changes in lifestyle are more important for future nutrient load projections than climate change. Especially in southern regions, lifestyle changes are responsible for the increasing nutrient loads to the Baltic Sea.

Societal changes can initiate shifts and trends in water quality through changes in N- and P-application and changes in land-use. A transition period in central and eastern Europe that occurred in 1989, called “the fall of the iron curtain” can be responsible for a shift to improved water quality. During the transition period (1989 - 2008), there were a lot of political and economic changes that resulted in: 1) a drop in artificial fertilizer and manure application, 2) a decrease in livestock stocking, 3) closure of several factories, 4) improvements in farm management practices and 5) modernization of wastewater treatment plants (Iital et al., 2005; Pastuzak and Igras, 2012b). Several studies investigated the water quality in rivers, seas and

lakes in terms of N- and P-load during the transition period (Hussian et al., 2003; Iital et al., 2005; Pastuzak and Igras, 2012b). Hussian et al. (2003) noted an almost linear downward trend of N carried by the Elbe river to the North Sea despite a dramatic decline of N-application in 1990 and then a slow increase. However, the decrease in total P-load was considerably smaller close to the mouth of the river than further upstream compared to the total N-load, likely because of changes in sedimentation rates and re-suspension of particulate matter. Iital et al. (2005) investigated changes in the amount of N and P in Estonian rivers during the transition period. They found a downward trend in the amount of N in 91% of the studied sites. A downward trend in the amount of P was observed in only 9% of the studied sites while also some upward trends were observed (9% of the studied sites).

### 1.3. Aim and research questions

The aim of this research is to quantify shifts and trends in water quality, specifically in N and P, in the BSDB and relate these shifts and trends to environmental, climatic and anthropogenic controls. To achieve this goal, a nutrient dataset of rivers flowing into the Baltic Sea will be combined with a dataset containing monthly data of temperature and precipitation for all catchments covering the entire measurement period. Moreover, current land-use will be added in order to get more insight in the possible controls that caused these shifts and trends.

The overarching research question in this study can be formulated as

'*Which anthropogenic and environmental mechanisms are responsible for the shifts and/or trends in the water quality of the catchments in the Baltic Sea Drainage Basin in the period 1970-2000?*'

To answer this research question, several sub-questions are formulated that will be answered in this report:

1. Which trends and shifts occurred in the catchments in terms of temperature, precipitation, river run-off and N and P (load and concentration)?
2. Does a trend or shift in temperature lead to a shift or trend in precipitation?
3. Does a trend or shift in precipitation lead to a trend or shift in flow?
4. To what extent can a trend or shift in N and P be related to a trend or shift in flow, precipitation or temperature?
5. To what extent can a trend or shift in N and P be related to societal changes in the transition period?
6. Can spatial differences in N and P be correlated to current land-use?

### 1.4. Hypotheses

Since climatic changes tend to have a higher impact in northern regions, I expect to see more positive trends in temperature in northern catchments than in southern catchments. However, I do not expect to find significant positive or negative shifts of temperature, as temperature will increase more gradually. If a positive trend in temperature is found, then I expect to see a positive trend for precipitation as in most cases precipitation increases with increasing temperature. This positive trend will be more pronounced in northern catchments than in southern catchments. Since precipitation is one of the major drivers of flow, I expect to find positive trends for flow in northern regions as well. To summarize, I expect to find climate-controlled positive trends for temperature, precipitation and flow. Moreover, this climatic control will be more pronounced in northern regions compared to southern regions. I do not expect to find positive or negative shifts of these variables as climate change involves more gradual changes rather than sudden changes.

Trends and shifts in N and P are more controlled by anthropogenic changes (e.g. the transition period) rather than climate change although I expect a small part of the trends and shifts to be explained by trends in flow and precipitation. In catchments where there is a positive trend for flow (and precipitation), I expect negative trends for N- and P-concentrations as N and P become more diluted. Note that this will not change the N- and P-loads. However, it is also possible to find the opposite, increasing flow can lead to increasing N- and P-concentrations by enhancing the uptake of N and P by rivers when more area is flooded (Arheimer and Lidén 2000). Therefore, it is very difficult to assess which effect increasing flow will have on N- and P-concentrations.

I expect anthropogenic controls to dominate trends and shifts of N and P. Increasing levels of N and P in the pre-transition period (1970-1988) are expected as a result of expansion of agricultural and urban area. However, differences will be observed among the catchments as not all catchments were influenced by land-use change. In contrast, several studies on water quality in the BSDB suggest decreasing levels of N during the transition period (1989-2000) for eastern countries (Hussian et al., 2003; Iital et al., 2005; Pastuzak and Igras, 2012b). Although the overall downward trend of N will be more or less the same for countries influenced by the transition period, I expect the timing of shifts to differ among catchments. However, no or little trends and shifts will be found for P that can be related to the transition period. Therefore, an east-west gradient along the BSDB is expected for N where eastern catchments influenced by the transition period show negative shifts and trends for N whereas western catchments not influenced by the transition period show no or positive shift and trends for N. Furthermore, I expect trends and

shifts in P to be more related to land-use changes, which will be more pronounced in the more populated catchments in the south.

I expect that spatial differences in trends and shifts of flow can be explained by land-use. In catchments with a greater percentage of wetlands, no trends or shifts will be observed, as wetlands are very resilient to changes in flow and precipitation. As a consequence, wetlands have less annual variability in flow than agricultural or forest-dominated catchments as wetlands can maintain high levels of discharges throughout the year (Lyon et al., 2012; Van der Velde et al., 2013). So, trends and shifts of flow are more likely to occur in urban, cultivated and forested areas. Furthermore, I expect that trends and shifts in N- and P-loads will correlate to land-use. Catchments that are mainly influenced by agricultural or artificial areas are more likely to have trends and shifts in terms of N- and P-concentration. Furthermore, wetlands act as a nutrient sink preventing N and P to be released to the rivers (Richardson et al., 1997). I expect patterns of trends and shifts in water quality due to land-use changes will closely follow patterns in population distribution in the BSDB. Since the southern catchments tend to be more populated, more trends and shifts due to land-use changes will be found in southern catchments.

To summarize, I expect anthropogenic controls to dominate trends and shifts in N and P (load and concentration) and thereby creating an east-west gradient within the BSDB. I expect environmental controls to dominate trends in flow (and to a minor extent also N and P) thereby creating a north-south gradient within the BSDB. Trends in temperature, precipitation and flow will be controlled by climatic changes and will show a north-south gradient within the BSDB.

## Chapter 2. The Survey Area

The Baltic Sea has little water exchange with the North Sea and, as a result, is more susceptible to anthropogenic impact compared to other, more open, seas (Pastuzak and Igras, 2012a). It is considered as one of the largest brackish water areas in the world with only salt water flowing in through the narrow Danish Straits, the Kategatt (Sörlin, 1982). There is a strong climate gradient from almost arctic conditions in the north to a more maritime climate in the south. Hence, catchments in the BSDB vary in their climatic, oceanographic and hydrologic characteristics (Graham and Bergström, 2001). The population in the catchment area of the Baltic Sea, the Baltic Sea Drainage Basin (BSDB), totals 85 million habitants divided over 14 countries. Most of these countries are highly industrialized and practice intense agriculture (Pastuzak and Igras, 2012b). The BSDB counts 634 catchments greater than 6 km$^2$ of which a large part remains un-monitored (Hannerz and Destouni, 2006). See figure 1 for a map of the survey area.

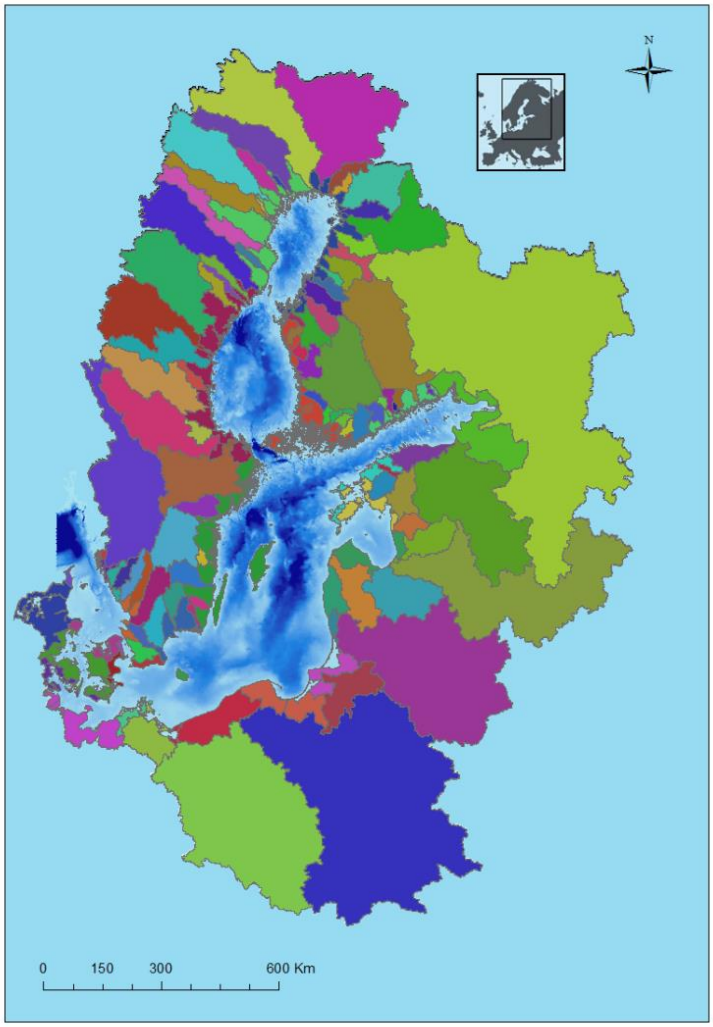


**Figure 1.** The Baltic Sea drainage basin.

## Chapter 3. Material and Methods

### 3.1. Sampling

The Baltic Nest Institute (BNI) dataset is based on data collected by the various national environmental agencies of the Baltic Sea nations (e.g. the Swedish Meteorological and Hydrological Institute, the state Hydrological Institute in St. Petersburg etc.). The Baltic Nest Institute (BNI) aims to facilitate adaptive management of environmental concern in the Baltic Sea. By modeling the entire drainage area, the BNI is implementing an ecosystem approach for a large marine ecosystem with a main focus on eutrophication and the flows of nutrients from land to sea (BNI, 2013). Time series of monthly flow and nutrient loads of dissolved inorganic nitrogen (DIN), TN, dissolved inorganic phosphorus (DIP) and TP are available for 84 catchments for the period 1970-2000. The other 33 catchments have data available for the period 1980-2000. Most of the water quality data came from sites close to the mouths of rivers (Stålnacke et al., 1998).

Monthly average values of temperature and precipitation of each catchment were obtained from the E-OBS gridded dataset (Haylock et al., 2008). This dataset can be downloaded free of charge from the website of the European Climate Assessment & Dataset (http://eca.knmi.nl). The collection of data was carried out by the Royal Netherlands Meteorological Institute (KNMI). A high resolution grid of $0.1^{o}$ (10 x 10 km) was obtained from roughly 250 weather stations (Haylock et al., 2008).

Land-use for the year 2000 in the BSDB was retrieved from the Corine Land-use dataset for European catchments. From catchments outside Europe, the Global Land Cover dataset was used. These two datasets were merged by the Baltic Nest institute. In this study, the fractions of eight types of land-use were extracted using ArcGIS 10.1. The types of land-use extracted are artificial (urban) areas, cultivated areas, deciduous forest, coniferous forest, mixed forest, shrubs and herbaceous area, wetlands and water bodies (rivers and lakes).

### 3.2. Data analysis

#### Dataset preparation

As a first step, temperature and precipitation from the E-OBS gridded dataset were added to the BNI-water quality dataset for each month in each catchment. Each month was labeled as 'snowmelt season' when temperature exceeded $1^{o}C$, or 'snow-accumulation season' when temperature was below $1^{o}C$. Next, the flow and the loads of DIN, TN, DIP and TP were calculated in $m^2$ by dividing with the catchment area. The concentrations of DIN, TN, DIP and TP were determined by dividing the loads of DIN, TN, DIP and TP with the flow. This prepared dataset

was used for statistical analysis based on the monthly average data. This dataset will be called MA.

Also, a yearly average dataset was constructed based on MA. An extra variable was added to this dataset that contains the number of months in the snowmelt season. This dataset will be called YA. Because seasonal effects are strong in the BSDB, one expects strong differences between the snowmelt season and the snow-accumulation season in terms of temperature, precipitation and flow (and thereby also have the potential to influence DIN, TN, DIP and TP). Therefore, two extra datasets were constructed of which one contains the yearly seasonal average of the snowmelt season and the other the yearly seasonal average of the snow-accumulation season. These datasets will be called YAM and YAA respectively.

Because there is a strong climate gradient from north to south and a societal gradient from east to west along the BSDB, all catchments were labeled as north or south and east or west. If the yearly average temperature exceeded 5°C, it was labeled as 'south'. Below that value, it was labeled as 'north' (Figure 2a). All catchments influenced by the transition period (catchments that were located at the east of the iron curtain) were labeled as 'east'. The remaining catchments as 'west' (Figure 2b).

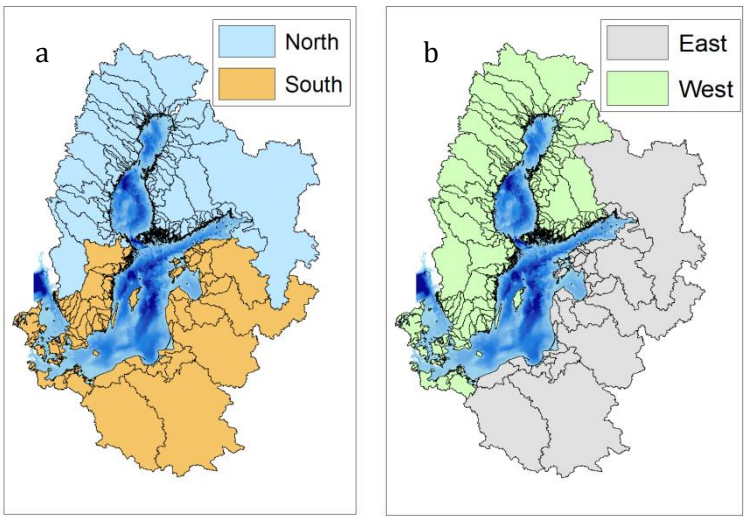


**Figure 2.** Showing the spatial distribution of catchment labeled as north/south (Figure 2a) and east/west (Figure 2b).

### (Seasonal) Mann-Kendall trend test

The Mann-Kendall trend test determines if a time-series contains a monotonic trend over time. It is a non-parametric test for randomness against time. This non-parametric test is preferred over a parametric test when testing for trends because it tends to ignore the magnitude of the

observations in favor of the relative values or ranks of the data. Moreover, a non-parametric test is distribution free and therefore fewer assumptions have to be made about the data (Hipel and McLeod, 2005). The Mann-Kendall trend test has the advantage that the power and significance are not affected by the actual distribution of the data (Hamed, 2009). The statistic can be described as:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(xj - xk)$$

$$\text{where } sgn(x) = \begin{cases} +1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases} \qquad \textit{Eq.}\ 1$$

A positive value for $S$ indicates that there is an upward trend whereas a negative value for $S$ indicates that there is a downward trend. Hence, the test determines whether $S$ is significantly different from zero (for $p < 0.05$). In fact, $S$ is a count of the number of times $x_j$ exceeds $x_k$ (See also *Eq.* 1). Note that the maximum value of $S$ occurs when $x_1 < x_2 < \ldots < x_n$.

This test will be applied on the temperature, precipitation, flow, DIN, TN, DIP and TP variables from the YA, YAA and YAM datasets for each catchment.

To check for trends in the MA dataset, a seasonal Mann-Kendall trend test has to be used. It is a multivariate extension of *Eq*. 1 for use with seasonal data. Under no trend conditions, the number of seasons, *m*, and the observations, *n*, are independent and identically distributed. The matrix of ranks (R) can be described as:

$$R = \begin{matrix} R11 & R12 & \ldots & R1m \\ R21 & R22 & \ldots & R2m \\ Rn1 & Rn2 & \ldots & Rnm \end{matrix}$$

Here, the observations for each season are ranked among themselves. The statistic can be described as:

*Eq.* 2

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(xjg - xkg), \quad g = 1,2,\ldots,m$$

This method was carried out in R using the package Kendall, freely available on the cran-server (see appendix A.1 for the R-script used in this research). For a more elaborate description of this static see Hipel and McLeod (2005).

For a visual representation, ArgGIS 10.1 was used where catchments with significant positive and negative trends were displayed. The difference in total area of catchments containing positive/negative trends among the two defined gradients (north/south and east/west) was tested for significance using the chi-square test. A Pearson correlation was used to extract correlation coefficients based on the slopes of the significant trends.

**Switch-point analysis**

The switch-point analysis used in this research closely follows the method described by Taylor (2000). First, the cumulative sum is calculated for the entire time-series. The next step is to determine the magnitude of change ($S_{diff}$):

$S_{diff} = S_{max} - S_{min}$ where

$S_{max} = \max S_i$ (i=0,….n)

$S_{min} = \min S_i$ (i=0,….n)

The method then generates a bootstrap sample of n units ($X^0_1$, $X^0_2$, $X^0_n$) by randomly reordering the n values. Then the bootstrap cumulative sum is calculated ($S^0_0$, $S^0_1$, $S^0_n$) upon which the maximum, the minimum and the difference of the bootstrap cumulative sum is determined. If the bootstrap difference is less than the original difference ($S_{diff}$), there is a shift (for $p < 0.05$).

Although the abovementioned description of the method can correctly identify shifts, it does not correct for trends. Hence, if the time-series is non-stationary, this likely can influence the results. Therefore, the model by Taylor (2000) was modified by first detrending the time-series and secondly fitting an auto-regressive moving-average (ARMA) model to the time-series, before generating a bootstrap sample. Moreover, this extended method excludes shifts that are happening at the start and at the end of the time-series (first and the last 3 years). See appendix A.2 for the R-script used in this research.

When the shifts were identified, the magnitude and direction of the shifts were determined by calculating the average change per year over a three-year time-period after the shift. A script in R was constructed that automated this step (Appendix A.3).

**Robust factor analysis**

Factor analysis is a tool to extract relationships from the data that represents immeasurable features of the data. The time-series data of the concentrations of DIN, TN, DIP, TP, flow and area were log-transformed. This transformation was not necessary for precipitation and

temperature, which were normally distributed. This method was carried out in R using the package StatDA. The R-script used in this research is based on the script constructed by Peter Filzmoser, and is freely accessible at statistik.tuwien.ac.at/public/filz/programs.html (See appendix A.4 for the R-script used in this research). For a more elaborate methodology about the statistics behind the ilr- and clr-transformations see Filzmoser et al. (2009b).

This method was applied to several different time periods for each dataset. First, the whole 31-year time period was taken to extract the most important relationships among temperature, precipitation, flow, DIN, TN, DIP and TP in 1970-2000. Then, a pre-transition time period (1970-1988) and a transition time period (1989-2000) were also taken to see if differences in factors (or the importance of factors indicated by the explained variance) exist between the two time periods. Moreover, the factors from these two time periods can also be checked with the factors of the bulk group. Analysis with these three time periods was repeated for five catchment groups: catchments labeled as north, south, east, west and a group which contains all the 117 monitored catchments.

To check if land-use influences temperature, precipitation, flow, DIN, TN, DIP and TP, eight land-use variables were included in the RFA for the period 1996-2000. Each of these variables contains the fraction of land that can be described by the type land-use. Since the land-use data contains information from the year 2000, it is assumed that no big changes in land-use occurred in the five-year period. This period was taken as a precaution to make sure any possible exceptional values of the year 2000 did not have a big influence on the robust factor analysis.

In all different time periods and groups, the loads of DIN, TN, DIP and TP were excluded from the analysis. This was done because the loads were calculated from the concentrations of DIN, TN, DIP and TP and the flow. Since these variables are included in the analysis, including the loads can give a wrong or confusing impression of the factor loadings.

## Chapter 4. Results

In this chapter, the results of the research are presented and divided in four sections. The first section describes the general characteristics of the dataset. This is essential for interpreting the importance of the results of the Mann-Kendall trend test (Section 4.2), the shift-point analysis (section 4.3) and the robust factor analysis (section 4.4).

### 4.1. General characteristics of the dataset

In table 1, the minimum, maximum, median and mean for each variable are noted. Some important characteristics of the BSDB are evident from this table. The average temperature of the BSDB is 4.4°C. Seasonal differences are evident as in YAM, the average temperature is 9.8°C while in YAA it is -4.2°C. There is also a notable difference between the two seasons for precipitation and flow. In YAM, it is on average raining 17 mm/month more compared to YAA. Subsequently, the flow in the catchments is lower in YAA (6 mm/month).

Since differences between average and median values are small for temperature, precipitation and flow, outliers do not have a big impact on the mean. This is not the case for the loads and concentrations of DIN, TN, DIP and TP, however. For these variables, the average is much higher than the median indicating that impact of outliers is substantial (note the difference between the maximum value and the median and mean for these variables). Therefore, the median reflects an average catchment better than the mean.

Differences in nitrogen and phosphorus are also evident. An average catchment transports 14 and 27 mg/m$^2$/month of nitrogen (DIN and TN respectively) while for phosphorus this is 0.4 and 1.0 mg/m$^2$/month (DIP and TP respectively). This is also the case for the concentration where 0.6 and 1.2 mg/L of nitrogen is present while for phosphorus it is 0.02 and 0.04 mg/L (DIP and TP respectively).

The generals characteristics showed in table 1 are also further separated by the four regions (Appendix B.1).

An independent two-sided t-test considering a significance level of 5% confirmed that there are significant differences for most variables between YAM and YAA:

- $p < 0.01$: Temperature, Precipitation, Flow, DIP and TP (load and concentration)
- $p < 0.05$: DIN concentration,
- $p > 0.05$: DIN load, TN (load and concentration)

Hence, nitrogen does not differ significantly between the two seasons (except for the concentration of DIN).

**Table 1.** Minimum, maximum, median and mean for all variables for the yearly average (YA), the yearly average in the snowmelt season (YAM) and the yearly average in the snow accumulation season (YAA).

| | | Minimum | | | Maximum | | | Median | | | Mean | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Unit** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** |
| **Temperature** | **°C** | -4.2 | 5.8 | -14.8 | 10.2 | 13.5 | 1.0 | 4.8 | 9.7 | -4.0 | 4.4 | 9.8 | -4.2 |
| **Precipitation** | **mm/month** | 27 | 26 | 1 | 92 | 105 | 122 | 49 | 56 | 38 | 50 | 56 | 39 |
| **Flow** | **mm/month** | 1 | 1 | 1 | 283 | 291 | 221 | 24 | 26 | 20 | 28 | 31 | 25 |
| **DIN** | **mg/ m²/month** | 0.3 | 0.1 | 0.3 | 1949 | 2002 | 1582 | 14 | 12 | 14 | 35 | 34 | 35 |
| **DIN** | **mg/L** | 0.03 | 0.01 | 0.01 | 8 | 8 | 11 | 0.6 | 0.6 | 0.7 | 1.2 | 1.1 | 1.2 |
| **TN** | **mg/ m²/month** | 1.2 | 0.9 | 0.9 | 2143 | 2201 | 1733 | 27 | 28 | 24 | 52 | 53 | 49 |
| **TN** | **mg/L** | 0.1 | 0.03 | 0.06 | 11 | 14 | 11 | 1.2 | 1.2 | 1.25 | 1.9 | 1.9 | 1.8 |
| **DIP** | **mg/ m²/month** | 0.005 | 0.002 | 0.002 | 58 | 59 | 48 | 0.4 | 0.4 | 0.3 | 1.1 | 1.1 | 0.9 |
| **DIP** | **mg/L** | 0.001 | 0.001 | 0.001 | 0.4 | 0.4 | 0.7 | 0.02 | 0.02 | 0.02 | 0.04 | 0.04 | 0.03 |
| **TP** | **mg/ m²/month** | 0.02 | 0.02 | 0.02 | 87 | 89 | 72 | 1.0 | 1.2 | 0.8 | 2.1 | 2.3 | 1.7 |
| **TP** | **mg/L** | 0.006 | 0.006 | 0.003 | 0.6 | 0.6 | 0.9 | 0.04 | 0.05 | 0.04 | 0.08 | 0.08 | 0.06 |

### 4.2. Mann-Kendall trend test

The output of the Mann-Kendall trend test is summarized in table 2. The results are divided in significant positive and negative trends. Moreover, a distinction is made in the location of the trend (north, south, east, west). Note that the four regions are based on two gradients: north/south and east/west. For each gradient, all catchments are used. Hence, each catchment is labeled with two locations: east or west and north or south

This analysis revealed significant trends for temperature in YA and YAM in all regions. Around 90% of the area of the BSDB shows a significant trend based on monthly average data. Temperature increase ranges between 0.01°C and 0.09°C per year (Figure 3a). The average increase in temperature is more or less the same for each region and is around 0.05°C per year (Table 2). From figure 3a, it becomes clear that temperature increased more in catchments located at the coast of the Baltic Sea compared to catchments located further away from the Baltic Sea.

For precipitation, mainly positive trends were found in YAA in the north. 61% of the area of the northern BSDB has a significant trend based on YAA data where there is an average increase of 0.4 mm/month/year (Table 2). The increase in precipitation ranges between 0.01 and 1.2 mm/month/year (Figure 3b).

Both positive and negative trends are revealed for flow. Positive trends are visible in the north while negative trends are visible in the south. More trends are found in YAA than in YAM.

The average increase in YAA for flow in the north is 0.4 mm/month/year (Table 2). Most of the trends are found in MA and range from 0.01 to 0.90 mm/month/year for positive trends and -0.01 to -1.52 for negative trends (Figure 3c).

**Table 2.** Summary table of the Mann-Kendall trend test. Trends are divided in four different locations. $A_{pos}/A_{neg}$ state the percentage of area that contains a positive/negative trend in the location (north, south, east, west). $\Delta_{pos}/\Delta_{neg}$ state the average change per year of all the positive/negative trends combined. Δ of temperature is in °C, Δ of precipitation and flow is in mm/month, Δ of the load of DIN, TN, DIP and TP is in μg/m²/month and Δ of the concentration of DIN, TN, DIP and TP is in μg/L.

| | North | | | | South | | | | East | | | | West | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $A_{pos}$ | $\Delta_{pos}$ | $A_{neg}$ | $\Delta_{neg}$ | $A_{pos}$ | $\Delta_{pos}$ | $A_{neg}$ | $\Delta_{neg}$ | $A_{pos}$ | $\Delta_{pos}$ | $A_{neg}$ | $\Delta_{neg}$ | $A_{pos}$ | $\Delta_{pos}$ | $A_{neg}$ | $\Delta_{neg}$ |
| **Yearly Average (YA)** | | | | | | | | | | | | | | | | |
| **Temperature** | 14 | 0.06 | 0 | - | 18 | 0.06 | 0 | - | 13 | 0.04 | 0 | - | 21 | 0.06 | 0 | - |
| **Precipitation** | 8 | 0.3 | 0 | - | 8 | 0.4 | 1 | - | 6 | 0.3 | 1 | - | 10 | 0.3 | 0 | - |
| **Flow** | 64 | 0.4 | 1 | - | 21 | 0.4 | 2 | - | 44 | 0.2 | 1 | - | 43 | 0.4 | 1 | - |
| **DIN load** | 22 | 271 | 39 | -272 | 5 | 732 | 40 | -1167 | 2 | - | 65 | -1024 | 36 | 284 | 6 | -379 |
| **TN load** | 22 | 431 | 4 | - | 12 | 980 | 36 | -1619 | 8 | 1287 | 31 | -1807 | 36 | 472 | 5 | -402 |
| **DIP load** | 9 | 34 | 35 | -26 | 39 | 23 | 15 | -18 | 32 | 33 | 41 | -13 | 8 | 27 | 6 | -28 |
| **TP load** | 15 | 43 | 7 | -41 | 50 | 21 | 1 | - | 72 | 24 | 0 | - | 12 | 39 | 8 | -32 |
| **DIN conc.** | 19 | 13 | 48 | -7 | 4 | - | 52 | -24 | 2 | - | 72 | -28 | 25 | 11 | 20 | -8 |
| **TN conc.** | 17 | 13 | 5 | -21 | 11 | 32 | 52 | -43 | 8 | 47 | 42 | -42 | 22 | 12 | 8 | -27 |
| **DIP conc.** | 13 | 0.8 | 47 | -0.8 | 41 | 1.4 | 1 | - | 33 | 1.6 | 29 | -0.3 | 18 | 0.8 | 20 | -0.9 |
| **TP conc.** | 42 | 1.2 | 24 | -0.9 | 55 | 1.9 | 4 | - | 75 | 1.6 | 1 | - | 14 | 1.5 | 32 | -0.9 |
| **Yearly seasonal Average Melt season (YAM)** | | | | | | | | | | | | | | | | |
| **Temperature** | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| **Precipitation** | 0 | - | 0 | - | 0 | - | 1 | - | 0 | - | 1 | - | 0 | - | 1 | - |
| **Flow** | 22 | 0.5 | 2 | - | 10 | 0.4 | 0 | - | 6 | 0.3 | 0 | - | 29 | 0.5 | 3 | - |
| **DIN load** | 19 | 309 | 39 | -313 | 3 | - | 47 | -1108 | 1 | - | 71 | -1246 | 24 | 297 | 7 | -156 |
| **TN load** | 18 | 537 | 3 | - | 11 | 922 | 15 | -2362 | 7 | 1514 | 13 | -2631 | 25 | 534 | 3 | - |
| **DIP load** | 6 | 38 | 35 | -35 | 36 | 26 | 17 | -22 | 30 | 43 | 43 | -20 | 9 | 30 | 6 | -35 |
| **TP load** | 42 | 58 | 6 | -51 | 47 | 25 | 3 | - | 70 | 34 | 2 | - | 12 | 49 | 7 | -43 |
| **DIN conc.** | 9 | 16.3 | 47 | -12 | 4 | - | 47 | -36 | 1 | - | 65 | -40 | 14 | 16 | 19 | -12 |
| **TN conc.** | 9 | 20.0 | 5 | -29 | 11 | 39 | 52 | -54 | 7 | 66 | 42 | -60 | 14 | 21 | 9 | -31 |
| **DIP conc.** | 3 | - | 44 | -1.0 | 36 | 1.5 | 15 | -1.0 | 31 | 1.5 | 41 | -0.7 | 3 | - | 16 | -1.1 |
| **TP conc.** | 36 | 1.9 | 13 | -1.5 | 41 | 2.3 | 3 | - | 65 | 2.3 | 1 | - | 3 | - | 16 | -1.4 |
| **Yearly seasonal Average Accumulation season (YAA)** | | | | | | | | | | | | | | | | |
| **Temperature** | 3 | - | 0 | - | 2 | - | 0 | - | 2 | - | 0 | - | 4 | - | 0 | - |
| **Precipitation** | 61 | 0.3 | 2 | - | 13 | 0.5 | 2 | - | 42 | 0.4 | 1 | - | 34 | 0.4 | 3 | - |
| **Flow** | 35 | 0.4 | 1 | - | 23 | 0.5 | 1 | - | 18 | 0.4 | 0 | - | 43 | 0.4 | 1 | - |
| **DIN load** | 29 | 512 | 36 | -113 | 6 | 880 | 11 | -848 | 3 | - | 38 | -487 | 37 | 504 | 6 | -108 |
| **TN load** | 35 | 623 | 3 | - | 13 | 1187 | 23 | -859 | 9 | 1629 | 20 | -859 | 45 | 662 | 3 | - |
| **DIP load** | 11 | 22 | 34 | -24 | 48 | 24 | 0 | - | 38 | 38 | 29 | -7 | 16 | 18 | 4 | - |
| **TP load** | 40 | 51 | 12 | -30 | 59 | 26 | 1 | - | 78 | 26 | 0 | - | 11 | 48 | 14 | -27 |
| **DIN conc.** | 13 | 21 | 44 | -3 | 6 | 52 | 11 | -65 | 5 | 57 | 38 | -36 | 16 | 21 | 16 | -2 |
| **TN conc.** | 18 | 21 | 3 | - | 13 | 63 | 0 | - | 11 | 68 | 0 | - | 22 | 22 | 3 | - |
| **DIP conc.** | 10 | 1.0 | 52 | -0.7 | 45 | 1.3 | 1 | - | 34 | 1.5 | 29 | -0.4 | 17 | 0.8 | 26 | -0.7 |
| **TP conc.** | 40 | 1.2 | 32 | -0.8 | 53 | 1.4 | 0 | - | 75 | 1.3 | 0 | - | 10 | 1.4 | 38 | -0.8 |
| **Monthly Average (MA)** | | | | | | | | | | | | | | | | |
| **Temperature** | 90 | 0.04 | 0 | - | 96 | 0.05 | - | - | 97 | 0.05 | 0 | - | 88 | 0.05 | 0 | - |
| **Precipitation** | 28 | 0.3 | 0 | - | 24 | 0.3 | 0 | - | 18 | 0.3 | 0 | - | 37 | 0.3 | 0 | - |
| **Flow** | 80 | 0.3 | 1 | - | 28 | 0.3 | 53 | -0.3 | 47 | 0.2 | 44 | -0.1 | 65 | 0.3 | 4 | -0.3 |
| **DIN load** | 37 | 223 | 47 | -83 | 15 | 448 | 63 | -1087 | 9 | 690 | 76 | -890 | 50 | 221 | 28 | -714 |
| **TN load** | 78 | 328 | 8 | -148 | 15 | 767 | 51 | -1457 | 37 | 992 | 40 | -1025 | 62 | 378 | 14 | -1268 |
| **DIP load** | 18 | 19 | 49 | -12 | 61 | 14 | 26 | -33 | 49 | 20 | 43 | -12 | 25 | 14 | 32 | -26 |
| **TP load** | 51 | 34 | 20 | -22 | 65 | 13 | 6 | -68 | 80 | 19 | 3 | -9 | 29 | 26 | 26 | -46 |
| **DIN conc.** | 25 | 9 | 50 | -5 | 14 | 42 | 78 | -17 | 10 | 80 | 86 | -22 | 33 | 9 | 35 | -8 |
| **TN conc.** | 64 | 9 | 13 | -12 | 13 | 73 | 56 | -24 | 37 | 96 | 42 | -33 | 42 | 9 | 22 | -12 |
| **DIP conc.** | 14 | 0.4 | 61 | -0.6 | 59 | 1.3 | 23 | -0.5 | 46 | 1.6 | 43 | -0.5 | 22 | 0.5 | 42 | -0.6 |
| **TP conc.** | 43 | 0.9 | 42 | -0.7 | 60 | 2.2 | 15 | -0.8 | 76 | 2.1 | 8 | -0.5 | 18 | 1.3 | 56 | -0.7 |

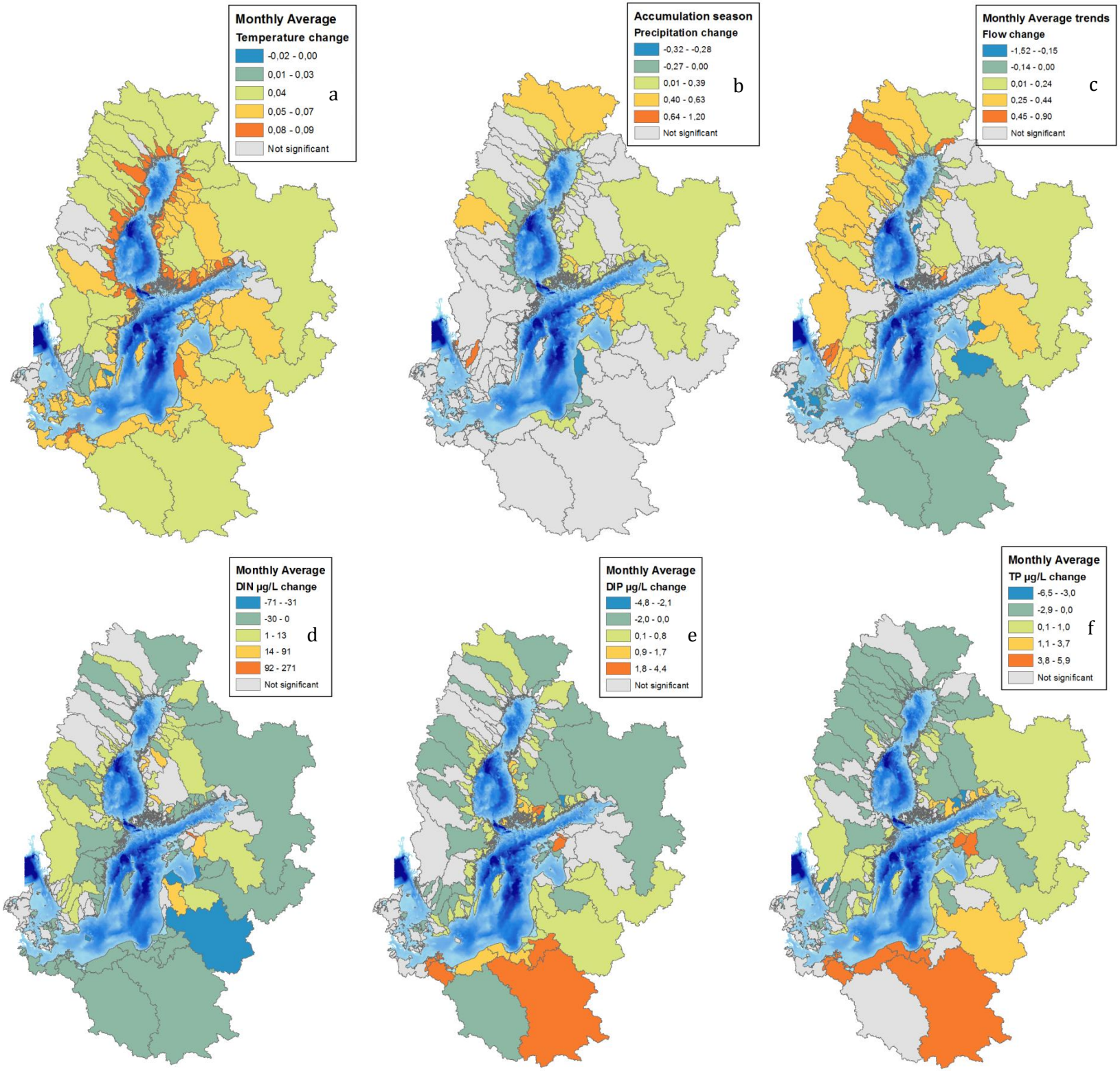


**Figure 3.** Significant changes of monthly average temperature in °C/month/year (a), precipitation in the snow accumulation season in mm/month/year (b), monthly average flow in mm/month/year (c) and monthly average DIN, DIP and TP concentration in µg/L/year (d, e, f respectively).

Before reporting detailed results of the loads and concentrations of DIN, TN, DIP and TP, some general remarks can be made. First, the pattern of the trends in load and concentration for each nutrient variable is more or less the same (Table 2). Second, the patterns of trends for DIN and TN are also more or less the same although differences in the average change per year exist. This is not the case for DIP and TP which have some notable differences. Third, patterns of trends for N are very different from those of P.

Most of the negative trends for DIN and TN are located in the east while some negative trends also occur in the west (Figure 3d). DIN tends to have more trends in the east than TN but the pattern remains the same: more negative trends in the east compared to the west. The average reduction per year for DIN in eastern catchments based on monthly average data is 22 μg/L and 890 μg/m$^2$/month. The average reduction per year for TN is 33 μg/L and 1025 μg/m$^2$/month. Also some positive trends for DIN and TN occur. Most of these trends occur in the west. The average increase per year for DIN in western catchments based on monthly average data is 9 μg/L and 221 μg/m$^2$/month. The average increase per year for TN is 9 μg/L and 378 μg/m$^2$/month.

Patterns for phosphorus are opposite to the nitrogen patterns. Most of the positive trends for DIP and TP are found in the east while most of the negative trends are found in the west. This difference is more pronounced for TP than DIP (Figure 3e and 3f). Furthermore, YAM reveals the least trends for DIP and TP whereas MA reveals most of the trends. The average increase per year for DIP in eastern catchments based on monthly average data is 1.6 μg/L and 20 μg/m$^2$/month. The average increase per year for TP is 2.1 μg/L and 19 μg/m$^2$/month. The average reduction per year for DIP in western catchments based on monthly average data is 0.6 μg/L and 26 μg/m$^2$/month. The average reduction per year for TP is 0.7 μg/L and 46 μg/m$^2$/month.

A chi-square test confirmed that there is a significant difference in the amount of trends in terms of area in DIN, TN, DIP and TP between east and west for MA and YA. In YAA, only DIP and TP are significant while in YAM, no significant difference between east and west is found. Furthermore, there is a significant difference in the amount of trends between north and south for precipitation in YAA only. For flow, the north-south difference is found for MA, YA, YAM and YAA.

Table 3 indicates if a trend in one variable also results in a trend in another variable for the same catchment if there are 10 catchments or more that have overlapping trends for all possible variable combinations. From table 3 it becomes clear that when the concentration of DIN, TN, DIP and TP increase, it is likely that the corresponding loads also increase. The highest agreement is found for DIN where in 78% of the catchments a positive trend for the load is

found when also a positive trend for the concentration is found. The nitrogen variables (load and concentration) show also considerable overlap. The same is found for the phosphorus variables (load and concentration). Table 3 also shows that a positive trend in flow likely results in a positive trend of the DIN, TN, DIP and TP loads. When a positive trend is found for temperature, in some cases a positive trend in DIN, TN, DIP and TP concentrations was seen. These results are not reflected for the negative trends however.

Table 3 shows that when a positive/negative trend in the concentrations or loads of DIN and TN occur, in many cases this result in a negative/positive trend in the concentrations or loads of DIP and TP. In other words, when a trend is found for a P variable, in many cases this results in a trend in the opposite direction for a N variable. Furthermore, when there is a positive trend for flow, in many cases this results in a negative trend for the concentrations of DIN, TN, DIP and TP. There are also some inverse trends found for precipitation and flow and temperature and flow.

**Table 3.** Percentage of the number of overlapping positive and negative trends (above gray-striped cells) and overlapping inverse trends (below gray-striped cells) between variables. Percentages of positive and negative trends are separated by a / sign. The first number represents the percentage of overlapping positive trends, the second number represents the percentage of overlapping negative trends. Bold cells represent variables of which more than 50% have overlapping trends. These results are based on trends identified from the yearly average.

| | Temp | Prec | Flow | DIN load | TN load | DIP load | TP load | DIN conc. | TN conc. | DIP conc. | TP conc. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **TP conc.** | 38/- | -/- | -/- | -/- | -/- | -/- | **56/-** | -/- | -/- | **50/71** | |
| **DIP conc.** | **50/-** | -/- | -/- | -/- | -/- | **50/-** | 42/- | 37/- | 32/- | | - |
| **TN conc.** | 45/- | -/- | -/- | **61/71** | **58/-** | -/- | -/- | **78**/39 | | 40 | **54** |
| **DIN conc.** | 44/- | -/- | -/- | **78**/36 | **67/-** | -/- | -/- | | - | 36 | **55** |
| **TP load** | 41/- | -/- | 44/- | 33/- | 31/- | **72/-** | | **50** | 33 | - | - |
| **DIP load** | -/- | -/- | **61/-** | -/- | -/- | | - | 39 | 42 | - | - |
| **TN load** | -/- | -/- | **66/-** | **83/-** | | - | - | - | - | 46 | **68** |
| **DIN load** | -/- | -/- | **50/-** | | - | - | 45 | - | - | 36 | **77** |
| **Flow** | -/- | -/- | | - | - | - | - | **61** | 40 | **50** | **67** |
| **Precipitation** | -/- | | **53** | - | - | - | - | - | - | - | - |
| **Temperature** | | - | **54** | - | - | - | - | 37 | - | - | - |

In order to get more insight whether the strength of the trend in one variable influences the strength of the trend in another variable, a Pearson correlation was done based on the slopes of all significant trends found in the MA dataset (Table 4). Since the loads of DIN, TN, DIP and TP are influenced by the flow, these variables were excluded in the Pearson correlation. The strongest positive correlation is found for DIN and TN (0.9) followed by a positive correlation for DIP and TP (0.8). This is in accordance with the results in table 3, where there is some considerable overlap among the nitrogen variables and among the phosphorus variables. Weaker, positive correlations are found for TP and TN (0.4), DIP and TN (0.4) and DIN and DIP (0.3). The strongest inverse correlation is found for temperature and precipitation (-0.7) meaning that when the change per year of a trend in precipitation increases, the change per year

of a trend in temperature decreases. Some other, weaker (but significant), inverse correlations are found for temperature and flow (-0.3) and flow and TP (-0.4).

**Table 4.** Results of the Pearson Correlation method based on the slopes of all significant trends based on monthly average data.

| | Temp | Prec | Flow | DIN conc. | TN conc. | DIP conc. | TP conc. |
|---|---|---|---|---|---|---|---|
| **TP conc.** | - | - | -0.4 | - | 0.4 | 0.8 | |
| **DIP conc.** | - | - | - | 0.3 | 0.4 | | 0.8 |
| **TN conc.** | - | - | - | 0.9 | | 0.4 | 0.4 |
| **DIN conc.** | - | - | - | | 0.9 | 0.3 | - |
| **Flow** | -0.3 | - | | - | - | - | -0.4 |
| **Precipitation** | -0.7 | | - | - | - | - | - |
| **Temperature** | | -0.7 | -0.3 | - | - | - | - |

### 4.3. Shift-point analysis

The output of the shift-point analysis is summarized in table 5. The results are divided in positive and negative shifts and are further separated in three different time periods: 1973-1980, 1981-1988 and 1989-1997. Since there is no clear pattern in the occurrence time of the shifts among the catchments, the results are not divided in north, south, east and west.

Positive shifts in temperature are observed in the period 1981-1988 in the YA and YAA datasets. Over a three-year period after the shift, temperature increased on average by 1.0°C in YA and 1.3°C per year in YAA. In YAA, negative shifts are observed for temperature in the period 1973-1980 where temperature decreased on average 0.9°C.

Positive shifts in precipitation are observed in YA (116 shifts), YAM (58 shifts) and YAA (55 shifts) divided over three time periods. While most of the shifts occur in the period 1973-1980, the strongest shifts occur in 1989-1997 where in YAA, the average strength of the shifts is 16.5 mm/month. The amount of negative shifts is far less than the amount of positive shifts. Most of the negative shifts occur in YAM in the period 1989-1997 where precipitation decreases with 5.7 mm/month.

In the period 1973-1980, many positive shifts were observed in the flow data in YA (31 shifts with an average increase of 2.6 mm/month), YAM (26 shifts with an average increase of 3.9 mm/month) and YAA (15 shifts with an average increase of 3.9 mm/month). Also some positive shifts occur in the other two periods but the number of shifts is less than observed during 1973-1980. On the contrary, negative shifts in flow are more evident in the last two time periods, especially in YA and YAM. In YAM, a reduction of flow is observed of 4.8 mm/month in the period 1981-1988.

In general, more shifts are found for the loads of DIN, TN, DIP and TP than for the concentrations. Differences in the number of shifts between the nitrogen and phosphorus variables are small. For the load of DIN, most positive shifts occur in 1973-1980 where in YAA

DIN load increases on average by 4178 μg/m²/month. Most negative shifts in the load of DIN occur in 1981-1988 where in YAM, DIN load decreases with 4856 μg/m²/month. For the concentration of DIN, most positive shifts occur in 1981-1988 where in YAM, DIN concentration increases on average with 132 μg/L. Most negative shifts in the concentration of DIN occur in 1981-1988 in YA and YAM (with a reduction of 124 and 191 μg/L respectively) but in 1989-1997 in YAA (with a reduction of 184 μg/L).

**Table 5.** Summary table of the shift-point analysis. The table is divided into positive and negative shifts and is further separated in three different time periods: 1973-1980, 1981-1988 and 1989-1997. N represents the significant number of positive/negative shifts that happened in a specific time period. Δ represents the mean change. Temperature is in °C, precipitation and flow in mm/month, the load of DIN, TN, DIP and TP in μg/m²/month and the concentration of DIN, TN, DIP and TP in μg/L.

| | Positive shifts | | | | | | Negative shifts | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1973-1980 | | 1981-1988 | | 1989-1997 | | 1973-1980 | | 1981-1988 | | 1989-1997 | |
| | N | Δ | N | Δ | N | Δ | N | Δ | N | Δ | N | Δ |
| **Yearly Average** | | | | | | | | | | | | |
| **Temperature** | 0 | - | 14 | 1.0 | 0 | - | 1 | -0.9 | 0 | - | 0 | - |
| **Precipitation** | 50 | 5.2 | 33 | 3.1 | 26 | 5.7 | 1 | -2.5 | 3 | -3.3 | 3 | -4.8 |
| **Flow** | 31 | 2.6 | 7 | 4.2 | 12 | 5.9 | 0 | - | 10 | -3.7 | 6 | -3.6 |
| **DIN load** | 16 | 3831 | 4 | 363 | 4 | 920 | 2 | -1932 | 13 | -5840 | 10 | -12737 |
| **TN load** | 16 | 5153 | 6 | 2066 | 14 | 6823 | 3 | -7771 | 14 | -7799 | 9 | -24509 |
| **DIP load** | 17 | 114 | 16 | 50 | 9 | 220 | 5 | -81 | 9 | -81 | 5 | -219 |
| **TP load** | 23 | 132 | 7 | 160 | 4 | 204 | 3 | -326 | 4 | -95 | 7 | -366 |
| **DIN conc.** | 6 | 49 | 6 | 24 | 0 | - | 8 | -147 | 13 | -124 | 11 | -175 |
| **TN conc.** | 4 | 95 | 8 | 130 | 7 | 181 | 6 | -201 | 9 | -180 | 3 | -462 |
| **DIP conc.** | 2 | 1 | 10 | 1 | 7 | 7 | 5 | -1 | 10 | -4 | 5 | -1 |
| **TP conc.** | 4 | 3 | 8 | 9 | 6 | 13 | 3 | -14 | 3 | -2 | 5 | -13 |
| **Yearly seasonal Average Melt Season** | | | | | | | | | | | | |
| **Temperature** | - | - | - | - | - | - | - | - | - | - | - | - |
| **Precipitation** | 35 | 7.0 | 13 | 6.5 | 10 | 9.3 | 0 | - | 4 | -2.9 | 7 | -5.7 |
| **Flow** | 26 | 3.9 | 12 | 5.9 | 4 | 4.5 | 1 | -2.4 | 12 | -4.8 | 7 | -4.1 |
| **DIN load** | 12 | 2156 | 6 | 2004 | 4 | 4745 | 5 | -2633 | 19 | -4856 | 8 | -10367 |
| **TN load** | 14 | 5960 | 13 | 6920 | 11 | 8812 | 6 | -13556 | 15 | -7504 | 7 | -13668 |
| **DIP load** | 12 | 110 | 16 | 87 | 9 | 263 | 6 | -228 | 13 | -115 | 2 | -144 |
| **TP load** | 16 | 227 | 13 | 275 | 5 | 380 | 1 | -1323 | 11 | -569 | 7 | -613 |
| **DIN conc.** | 3 | 77 | 12 | 132 | 9 | 131 | 5 | -153 | 10 | -191 | 8 | -129 |
| **TN conc.** | 8 | 282 | 13 | 124 | 11 | 225 | 14 | -155 | 2 | -248 | 6 | -328 |
| **DIP conc.** | 8 | 6 | 14 | 4 | 10 | 5 | 9 | -3 | 7 | -7 | 4 | -4 |
| **TP conc.** | 8 | 7 | 9 | 11 | 12 | 12 | 5 | -17 | 10 | -5 | 7 | -14 |
| **Yearly seasonal Average Accumulation Season** | | | | | | | | | | | | |
| **Temperature** | - | - | 26 | 1.3 | 0 | - | 13 | -0.9 | 0 | - | 0 | - |
| **Precipitation** | 19 | 4.9 | 32 | 4.8 | 4 | 16.5 | 0 | - | 1 | -4.2 | 2 | -7.3 |
| **Flow** | 15 | 3.9 | 3 | 3.7 | 11 | 6.6 | 1 | -1.7 | 3 | -4.6 | 4 | -7.7 |
| **DIN load** | 16 | 4178 | 5 | 3591 | 10 | 5192 | 1 | -2050 | 6 | -8553 | 4 | -5876 |
| **TN load** | 8 | 7569 | 14 | 4719 | 14 | 7482 | 1 | -11900 | 3 | -14167 | 4 | -8994 |
| **DIP load** | 5 | 222 | 14 | 367 | 9 | 46 | 4 | -88 | 1 | -186 | 8 | -262 |
| **TP load** | 12 | 211 | 10 | 197 | 3 | 107 | 1 | -237 | 11 | -351 | 5 | -258 |
| **DIN conc.** | 6 | 149 | 12 | 104 | 11 | 181 | 3 | -339 | 2 | -540 | 7 | -184 |
| **TN conc.** | 7 | 52 | 16 | 254 | 15 | 269 | 6 | -726 | 2 | -963 | 1 | -328 |
| **DIP conc.** | 3 | 4 | 16 | 6 | 8 | 2 | 5 | -9 | 7 | -9 | 6 | -6 |
| **TP conc.** | 8 | 4 | 17 | 8 | 7 | 19 | 4 | -8 | 7 | -20 | 5 | -9 |

For the load of TN, positive shifts occur in all three time periods in YA, YAM and YAA. The strongest shifts occur in YAA in the period 1973-1980 (7569 μg/m$^2$/month) and 1989-1997 (7482 μg/m$^2$/month). Most negative shifts in the load of TN occur in 1981-1988 although the strongest shifts occur in 1989-1997, where in YA DIN load is on average reduced by 24509 μg/m$^2$/month. For the concentration of TN, most positive shifts occur in 1981-1988 where in YAA, TN concentrations increase on average by 254 μg/L. The strongest negative shifts in the concentration of TN occur in 1989-1997 where TN reduces with 462 μg/L in YA and 328 μg/L in YAM and YAA.

For the load of DIP, most positive shifts occur in 1981-1988 where in YAA, DIP load increases on average by 367 μg/m$^2$/month. Most negative shifts in the load of DIP occur in 1981-1988 for YA and YAM (with on average a strength of 81 and 115 μg/m$^2$/month respectively) and in 1989-1997 for YAA (with on average a strength of 262 μg/m$^2$/month). For the concentration of DIP, most positive shifts occur in 1981-1988 where in YAA, DIP concentrations increase on average by 6 μg/L. The strongest negative shifts in the concentration of DIP occur in 1973-1980 and 1981-1988 in YAA with a reduction of 9 μg/L.

Most positive shifts of TP occur in 1973-1980 where in YAM, TP load increases on average by 227 μg/m$^2$/month. Most negative shifts in the load of TP occur in 1981-1988 where the strongest shifts happen in YAA (an average reduction of 569 μg/m$^2$/month in 1981-1988). For the concentration of TP, most positive shifts occur in 1981-1988 where in YAA, TP concentrations increase on average by 8 μg/L. However, the strongest positive shifts can be found in the period 1989-1997 where in YAA, TP is increased by 16 μg/L. Most negative shifts in the concentration of TP occur in 1981-1988 in YAM and YAA (with an average reduction of 5 and 20 μg/L respectively) but in 1989-1997 in YA (with an average reduction of 13 μg/L).

Because the shifts are scattered among the BSDB, not much overlap is found among the variables within the catchments. Only in YA in the period 1973-1980 some considerable overlap was found. In general, a shift in precipitation is associated with a shift in flow and the loads of DIN, TN, DIP and TP. Furthermore, when a shift in one N variable occurs, this also results in a shift in the other N variable. The same is true for P. However, these observations are neither found in the other time periods nor in YAM and YAA.

### 4.4. Robust factor analysis

Robust factor analysis was carried out for four different periods (1970-2000, 1970-1988, 1989-2000 and 1996-2000) divided in five different groups based on their location: north, south, east, west and all catchments together. Table 6 and figure 4 present an example of the output of the analysis based on all catchments and for the time period 1996-2000. The factor matrix (Table 6)

gives an overview of the loadings of each variable for all three variables. Moreover, also the communality of each variable is indicated. The communality tells how well the variables are explained by the three factors combined. Positive and negative loadings within a factor indicate that there is an inverse relationship between the positive and negative loaded variables. Variables with a factor loading between -0.5 and 0.5 are ignored in order to get a clear view about what each factor signifies (the closer to 1 or -1, the more important the variable for the factor is). From table 6 it becomes clear that the first factor consists of two elements (negative and positive) and explains 47% of all the variance in the dataset. Wetlands and shrubs and herbs are correlated with each other and have an inverse relationship with artificial area, cultivated area, temperature DIN and TN (which also are correlated with each other). The second factor explains 16% of the variance in the dataset and consists of two elements. DIN, TN, DIP, TP and mixed forest are correlated with each other and have an inverse relationship with coniferous forest and waterbodies. These two factors are graphically represented in a biplot (Figure 4). The third factor explains 10% and consists of two elements in which deciduous forest has an inverse relationship with TP. The robust factor analysis for this group explains in total 73% of the variance. It can explain the variance of DIP the best, with a communality of 0.98 and precipitation and flow the least, with a communality of 0.11.

Table 7 summarizes all robust factor analyses that were carried out for four different time periods for all four datasets. The time periods 1970-2000 and 1970-1988 show the same factors. The time-period 1989-2000 is different because it shows an extra P factor in YAM. The most important factor consists of one element. DIN, TN, DIP and TP are correlated with each other. This important factor explains between 39% in YAM to 61% in YAA in the period 1989-2000. In the second factor, DIN and TN are correlated with each other and in some cases also with temperature. This means that when temperatures are higher, more N is present in the catchments. This factor is not visible in MA, however. Here, the second factor consists of one element in which precipitation and temperature are correlated with each other. The third factor consists of one element in which precipitation and flow are correlated with each other. In YAA, this relationship is more important compared to YA and YAM and comprises the second factor.

**Table 6.** Factor matrix from robust factor analysis for the period 1996-2000 based on yearly average data. Values in the factor columns represent the loadings of the variables. Cells marked in orange are discarded in further analysis. The communality represent the fraction of variance of a variable that is explained by this matrix.

| Expl. cum. variance | 47 | 63 | 73 | |
|---|---|---|---|---|
| Explained variance | 47 | 16 | 10 | |
| | Factor 1 | Factor 2 | Factor 3 | Communality |
| DIN | 0.79 | 0.55 | -0.14 | **0.95** |
| TN | 0.76 | 0.58 | -0.16 | **0.95** |
| DIP | 0.42 | 0.80 | -0.40 | **0.98** |
| TP | 0.48 | 0.64 | -0.51 | **0.90** |
| Precipitation | 0.25 | -0.02 | 0.23 | **0.11** |
| Flow | -0.26 | -0.05 | 0.19 | **0.11** |
| Temperature | 0.91 | 0.06 | 0.12 | **0.84** |
| Area | -0.31 | -0.04 | 0.45 | **0.30** |
| Artificial area | 0.82 | 0.27 | -0.16 | **0.77** |
| Cultivated area | 0.87 | 0.43 | -0.12 | **0.96** |
| Deciduous forest | 0.01 | -0.09 | 0.82 | **0.68** |
| Mixed forest | -0.23 | 0.78 | -0.25 | **0.72** |
| Coniferous forest | 0.10 | -0.87 | -0.27 | **0.84** |
| Shrubs and herbs | -0.87 | 0.16 | 0.20 | **0.81** |
| Wetlands | -0.81 | 0.07 | 0.07 | **0.66** |
| Waterbodies | -0.25 | -0.59 | 0.04 | **0.41** |

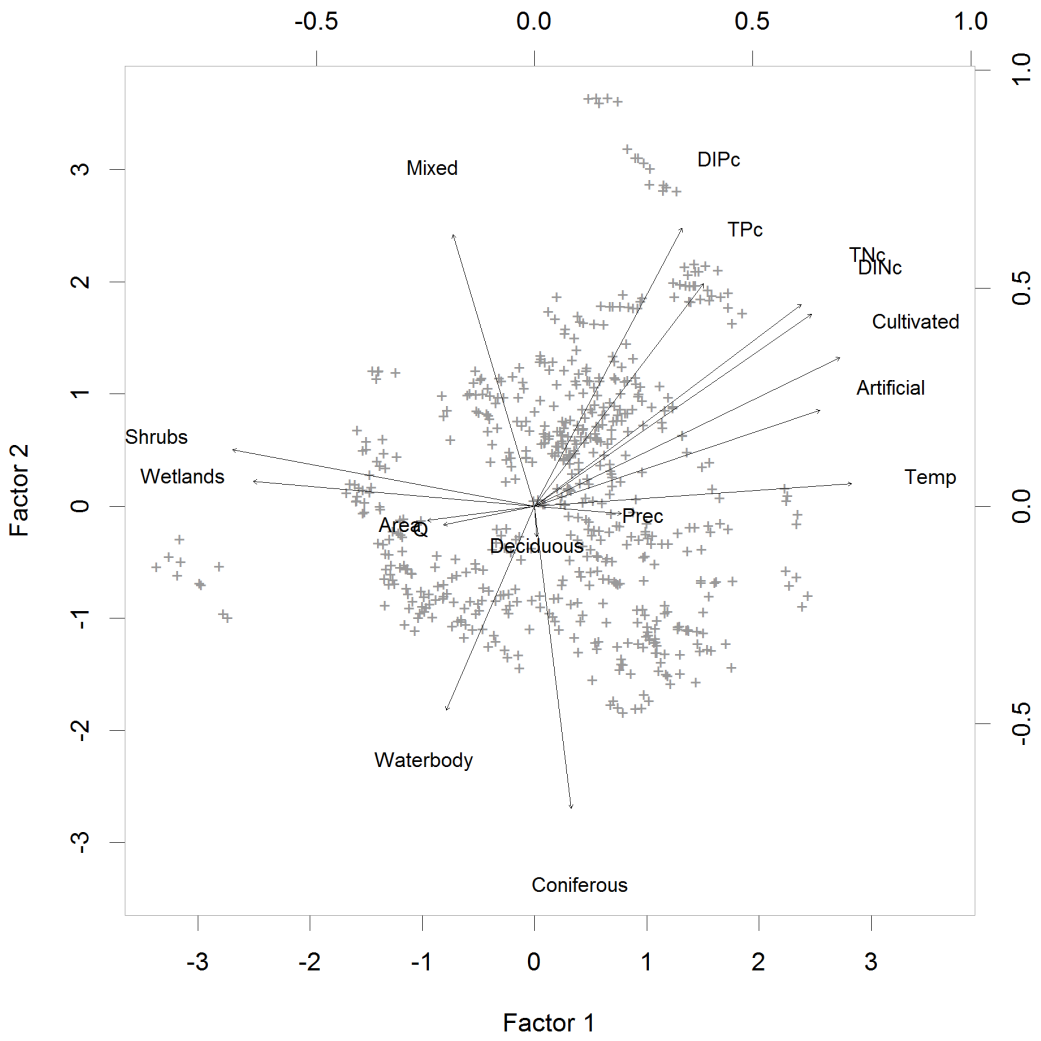


**Figure 4.** Biplot of factor 1 (x-direction) and factor 2 (y-direction) based on the factor matrix in table 7. Upper and right axis represent the factor loadings (depicted as arrows), lower and left axis represent factor scores (depicted with +-signs).

**Table 7.** Results of the robust factor analysis divided over four different time periods: 1970-2000, 1970-1988, 1989-2000 and 1996-2000. Element 1 and 2 in the same row represent one factor and have an inverse relationship. Variables in brackets indicate that the corresponding loadings in some cases are just below 0.5 (or above -0.5). Values in the last four columns represent the explained variance of the factor. Cells colored in dark-green represent the 1st factor, green the 2nd factor and light-green the 3th factor.

| Period | Element 1 | Element 2 | YA | YAM | YAA | MA |
|---|---|---|---|---|---|---|
| 1970-2000 | (DIN), TN, DIP, TP | | 58 | 45 | 53 | 44 |
| | DIN, TN, (Temperature) | | 18 | 18 | 12 | |
| | Precipitation, Flow | | 10 | 12 | 19 | |
| | Precipitation, Temperature | | | | | 15 |
| | | | | | | |
| 1970-1988 | (DIN), TN, DIP, TP | | 58 | 44 | 44 | 43 |
| | DIN, TN, (Temperature) | | 18 | 19 | 11 | |
| | Precipitation, Flow | | 10 | 12 | 18 | |
| | Precipitation, Temperature | | | | | 18 |
| | | | | | | |
| 1989-2000 | (DIN), TN, DIP, TP | | 61 | 39 | 56 | 45 |
| | DIN, TN, (Temperature) | | 17 | | 13 | |
| | Precipitation, Flow | | 9 | 13 | 18 | |
| | DIP, TP | | | 19 | | |
| | Precipitation, Temperature | | | | | 16 |
| | | | | | | |
| 1996-2000 | DIN, TN, (Temperature), Cultivated area, Artificial area | Wetlands, Shrubs and herbs | 47 | 41 | | 40 |
| | DIN, TN, DIP, TP, Mixed forest | Coniferous forest, waterbodies | 16 | 16 | | |
| | (DIP), TP | Deciduous forest, (Area) | 10 | 11 | | |
| | DIN, TN, DIP, TP, Temperature, Cultivated area, Artificial area | | | | 44 | |
| | DIP, TP, Mixed forest | Coniferous forest, waterbodies | | | 17 | |
| | Deciduous forest | | | | 11 | 9 |
| | Mixed forest, shrubs and herbs, wetlands | | | | | 11 |

When land-use variables are included in robust factor analysis (in the period 1996-2000) differences among the four datasets appear. The first three factors in table 7 for the time period 1996-2000 are also described by table 6. YAA is different from YA and YAM and has different factors. In YAA, DIN, TN, DIP, TP and temperature are correlated with cultivated and artificial area and comprises the most important factor (explained variance is 44%). In the second factor, DIP and mixed forest are inversely correlated with coniferous forest and waterbodies (17% of explained variance). In the third factor the inverse correlation of DIP and deciduous forest disappears. Here, deciduous forest is the only variable in this factor.

Table 8 summarizes all robust factor analyses that were carried out for three different time periods separated in north, south, east and west. Differences in the kind and importance of factors among the four different locations become visible. In YA, the northern and western

catchments show the same factors. They are different from the southern and eastern catchments. In eastern catchments, the factor analysis distinguish a nitrogen factor from a phosphorus factor with nitrogen being more important than phosphorus.

In YAM, northern and southern catchments show more or less the same factors. This is also true for east and west. The difference between the two gradients is that in the east/west gradient, the factor analysis is able to distinguish a nitrogen variable from a phosphorus variable, which are grouped together in the northern and southern catchments. An important difference is noted when the transition period is compared with the pre-transition period in east and west. In the transition period, the phosphorus variable becomes more important (43% of explained variance) compared to the pre-transition period (18-19% of explained variance).

In YAA, northern, southern and western catchments show more or less the same factors. Eastern catchments show the same factors as in YAM. Here, the phosphorus factor also becomes more important in the transition period.

**Table 8.** Results of the robust factor analysis divided over three different time periods: 1970-2000, 1970-1988 and 1989-2000 which are further divided in four different groups (north, south, east, west). Element 1 and 2 in the same row represent one factor and have an inverse relationship. Variables in brackets indicate that the corresponding loadings in some cases are just above -0.5. Values in cells represent the explained variance of the factor. Cells colored in dark-green represent the 1st factor, green the 2nd factor and light-green the 3th factor.

| | | YA | | | | | | | | | | | | YAM | | | | | | | | | | | | YAA | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | North | | | South | | | East | | | West | | | North | | | South | | | East | | | West | | | North | | | South | | | East | | | West | | |
| **Element 1** | **Element 2** | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 | 1970-2000 | 1970-1988 | 1989-2000 |
| DIN, TN, DIP, TP | (Area) | 63 | 63 | 62 | 40 | | 42 | | | | 60 | 59 | 63 | 56 | 53 | 53 | 46 | 47 | 45 | | | | | | | 60 | 58 | 63 | 46 | 44 | 45 | | | | 56 | 56 | 58 |
| Temperature, DIN, TN | | 17 | 17 | 17 | | | | | | | 17 | 17 | 16 | | | | | | | | | | | | | | | | | | | | | | | 9 | |
| Precipitation, Flow | (Area) | 7 | 7 | 8 | 24 | 11 | 24 | 12 | 12 | | 11 | 11 | 10 | 17 | 17 | 11 | 22 | 22 | 23 | | | | 12 | 12 | 13 | 18 | 19 | 17 | 24 | 25 | 26 | 9 | 10 | 9 | 19 | 19 | 19 |
| Area | (Temperature) | | | | 15 | | | | | 11 | | | | | | | | | | | | | | | | 8 | 8 | 7 | 10 | 11 | 11 | | | | | | |
| DIN, TN | (Area) | | | | | 46 | | 35 | 34 | 38 | | | | | | 17 | | | | 38 | 35 | 18 | 45 | 47 | 19 | | | | | | | 38 | 42 | 30 | | | |
| DIP, TP | | | | | | 22 | | 24 | 29 | 24 | | | | | | | | | | 23 | 25 | 43 | 20 | 20 | 43 | | | | | | | 31 | 25 | 40 | | | |
| DIP | | | | | | | 14 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Temperature, Area | | | | | | | | | | | | | | | | | 14 | 11 | 13 | | | | | | | | | | | | | | | | 9 | | |
| Flow | Area | | | | | | | | | | | | | | | | | | | 13 | 15 | 13 | | | | | | | | | | | | | | | |

## Chapter 5. Discussion

### 5.1. Interpretation of the results

This study shows that splitting the dataset into YAM and YAA gave more information about the variables used as not only temperature or precipitation, but also DIP and TP are significantly different between the two seasons. However, differences among catchments within YAA and YAM are still substantial as catchments in the BSDB vary in their meteorological, oceanographic and hydrologic characteristics (Graham and Bergström, 2001). The fact that the load and concentration of the phosphorus variables are significantly different between the two seasons, suggests that a climatic control exists on the distribution of this nutrient. This is not the case for the nitrogen variables however.

A temperature increase was observed in a large part of the BSDB ranging from 0.01°C to 0.09°C per year when fitting a linear regression to the data over time. The International Panel of Climate Change (IPCC) reported that the global average air temperature increased by 0.013°C per year in the period 1956-2005 (Trenberth et al., 2007). Furthermore, the IPCC stated that temperature increase is higher in northern regions which is confirmed by this study. The higher increase nearby the coast can have two explanations. First, warming of Baltic Sea water could influence temperatures in coastal sea regions. From literature it was found that Baltic Sea water indeed warmed in the past 50 years (Feistel et al., 2004; Boesch et al., 2006; Alheit et al., 2012). Second, due to temperature increase, the time per year that northern parts of the Baltic Sea are covered with ice decreases which results in a temperature increase in coastal regions due to a lengthening of exposure to sea water. Although slight variations in air temperature have a big impact on sea ice cover in the Baltic Sea, the direction and strength of the wind play a more crucial role in sea ice dynamics of the Baltic Sea as they tend to break and fragment ice-cover (Herman et al., 2011). The North Atlantic Oscillation (NAO) causes stronger winds in the Baltic Sea region during a positive NAO-phase (Schimanke, 2012) and also increases sea surface temperatures (SST) of the Baltic Sea (Alheit et al., 2012). Therefore, it is plausible that warming of Baltic Sea water and/or reduced sea ice cover is responsible for the higher temperature trends in coastal northern catchments. The influence of NAO in the BSDB becomes clearer when the shifts of temperature in YAA are investigated. 26 positive shifts of temperature were found in the period 1981-1988 with all shifts occurring in 1987 or 1988. According to Alheit et al. (2004), NAO is responsible for changes in temperature and wind-direction in the BSDB during winter in the late eighties when a transition occurred from a negative to a positive NAO phase.

For precipitation, mainly positive trends were found in northern regions with an average change of 0.4 mm/month/year for YAA with most shifts for the period 1981-1988. Hurrel (1995) stated that a positive NAO phase resulted in increased winter precipitation in Scandinavia. Again, the transition from a negative to a positive phase of NAO might be responsible for the shifts found in YAA in the period 1981-1988. However, many shifts of precipitation are found in the YA and YAM dataset for the period 1972-1980. Therefore, NAO cannot explain all the trends and shifts found for precipitation. The IPCC reported that it is likely that precipitation increased in northern Europe as increases in temperature lead to increases in the moisture-holding capacity of the atmosphere (Trenberth, 2007). Furthermore, this study found that when the change in temperature increases, the change in precipitation decreases. Moreover, precipitation trends are more pronounced in regions where temperature change is less. At some parts at the coast, precipitation shows decreasing trends. Hence, warming and NAO are both responsible for the shifts and trends for precipitation in the northern BSDB.

A gradient in flow is observed with positive trends in the north and negative trends in the south. Both temperature and precipitation influence flow as increased temperatures enhance evaporation thereby decreasing the flow. Increased precipitation results in more run-off thereby increasing the flow. These results show that northern catchments away from the coast show high increase in flow. In these catchments, temperature change is low and precipitation change is high. In the southern catchments where temperature change is low or moderate (increase between 0.01-0.03$^{o}$C per year) and precipitation change is not present, flow shows a negative trend. Hence, this gradient is explained by the distribution of trends of temperature and precipitation. Future scenarios for flow in the Stockholm region predict an increase in flow of 3-22% in 2100. Although the different scenarios are variable in terms of increase, the prevailing pattern is the same and point to increased winter flow (Moore et al., 2008). Kjellström and Ruosteenoja (2007) investigated future simulated changes in precipitation and flow over the entire Baltic Sea region and found that during summer, increased precipitation in the north is contrasted with a decrease in the south of this region resulting in increased flow in the north and decreased flow in the south. The results of Kjellström and Ruosteenoja (2007) suggests that the results for the trends in flow found in this study will stay the same until the year 2100.

A positive trend in flow results in turn to a positive trend in loads of DIN, TN, DIP and TP. However, for the concentrations, it is the opposite as concentrations are diluted when the flow increase. The southern and eastern catchments show strong negative trends for DIN (load and concentration) over time. This is good evidence that eastern countries reduced DIN substantially

over time. Note that 80% of the southern catchments are also labeled as east. Although the transition period is a likely candidate in explaining this observation, the amount of negative shifts for DIN is not supportive. Based on the YA dataset in the period 1989-1997, only 11 negative shifts were found for the load of DIN and 10 negative shifts for the concentration of DIN, scattered throughout the BSDB. One possibility for this observation is that the shifts of DIN caused by the transition period were not strong enough to be detected by shift-point analysis. Another possibility is that the shifts occurred after 1997. The transition period lasted till 2008 so this is a realistic explanation. However, the fact that many negative, strong trends are found for DIN with an absence of shifts for DIN in eastern catchments suggests that reductions in DIN was an ongoing process without sudden changes. Indeed, from models it was concluded that nitrogen loads decreased substantially from the 1980s onward in all parts of the BSDB (HELCOM, 2011). The same story can be told for TN although in eastern and southern catchments, more negative trends occur for TN when compared to DIN.

Changes in positive and negative trends for DIN and TN are probably caused by changes in diffuse sources (HELCOM, 2011). Among the diffuse sources, agricultural activities are most responsible for these changes so either or both land-use changes or changes in agricultural practices are responsible for the changes found for nitrogen. From our robust factor analysis, it is concluded that N and P have an inverse relationship with the size of the catchment area in all locations. According to Smith et al. (2003) the area effect for nitrogen is explained by the inter-catchment heterogeneity among small catchments in terms of land-use. Land-use is more variable among small catchments than among large catchments. Therefore, land-use change can have a big impact in catchments, which are small in size. A likely candidate that explains this observation is that land-use change occurred close to the coast, where catchments are small in size. When land-use is included in robust factor analysis, it follows that nitrogen is correlated with cultivated area and artificial area. Hence, conversion of land into cultivated area has a big impact on nitrogen. The inverse relationship to wetlands confirms that wetlands are important for nitrogen retention (Richardson et al., 1997) and that cultivated and artificial areas came at a cost of wetland areas. Jansson et al. (1998) calculated that wetlands in the BSDB retain nitrogen corresponding to 5-13% of the annual total amount of nitrogen entering the BSDB. In the melt season, these changes also affect flow as flow decreases when artificial and cultivated areas increase (Table 7). Moreover, the land-use variable shrubs and herbs seems also important for nitrogen retention. Despite the fact that no land-use variables exist for the period before 1996, it is expected that the found relationship will be the same for the whole period. Pulling these results together, it is likely that positive trends and shifts in nitrogen (DIN and TN concentrations) are the result of increasing cultivated and artificial areas at the expense of

wetland areas and shrubs and herbs. Negative trends and shifts can have multiple explanations. Improvements in farm management practices and agricultural technologies might lead to reductions in nitrogen loads and concentrations. These changes are more gradual than sudden so it is logical that more negative trends than shifts are found for nitrogen. Moreover, eastern countries had a lot to improve in their agricultural technology (Pastuzak and Igras, 2005) and might explain the overrepresentation of negative trends in eastern catchments. Furthermore, constant pressure by the Baltic Sea Joint Comprehensive Environmental Action Program (JCP) on these countries reduced their anthropogenic sources of nitrogen and phosphorus (JCP, 1993). This might have induced changes before the transition period making these changes more gradual rather than sudden.

The trends found for the phosphorus variables show the opposite pattern when compared to the trends for the nitrogen variables. Positive trends for DIP and TP dominate the east (and south) while negative trends dominate the west (and north). Like for nitrogen, no clear pattern is observed for phosphorus concerning the shifts. Most shifts for DIP occur in 1981-1988 while for TP most shifts occur in 1973-1980. Negative trends in western catchments can be explained by an increasing share of wastewater being treated and by implementing more advanced treatment techniques in municipal and industrial facilities (HELCOM, 2011). Moreover, closure of heavily polluting factories and an increased use of phosphorus-free detergents also helped in reducing phosphorus loads to the Baltic Sea. Most of these facilities are located in smaller catchments near the coast (populous areas) and explain the area effect for P previously discussed. From 1975 onwards, these improvements were applied by Denmark, Germany, Lithuania and Sweden, mainly western countries (except for Lithuania). In 1985, phosphorus loads from point source discharges were already cut to a third. These point source discharge-related improvements had a stronger impact on phosphorus than nitrogen. This might explain why more negative trends in the west are found for phosphorus than for nitrogen (were more positive trends were found). Ærtebjerg et al. (2003) found that input of phosphorus had been reduced by 90% in the Danish Straits after these improvements while nitrogen was reduced by only 30%. In the eastern countries, Estonia, Latvia and Poland, reduction of phosphorus from point source discharges started after the transition period. In this study, it was found that factors associated with P became more important in eastern catchments in the transition period. Although, from 1989 onward, phosphorus loads to the Baltic Sea was reduced, the major reductions happened after 2005, when these countries accessed the EU (HELCOM, 2011). The Helsinki Commission reports that there is still some great potential to reduce phosphorus inputs from point sources (HELCOM, 2007). The reason, why positive trends for DIP and TP are found in eastern countries

are twofold. First, big reductions of phosphorus did not start until the 2000s, for which no data is available. Second, gradual increase of phosphorus in the 1970s dominates the gradual (small) decrease in the 1990s.

Not only point-sources influence phosphorus levels. When land-use variables are included in robust factor analysis, it is revealed that DIP and TP have an inverse relationship with deciduous forest. In YAA, this inverse relationship is found for coniferous forest. This suggests that deciduous forest soils lose most of their P retaining function during winter (no P uptake in winter of deciduous trees). In winter, uptake of P continues in coniferous trees and explains the presence of this factor in YAA. Apparently, forests are important in retaining phosphorus. Indeed, it was found that forest soils in Scandinavia are retaining P due to the enrichment of Al and Fe compounds in the B horizon of podzolic soils and peatlands to which P can be adsorbed (Väänänen, 1998).

### 5.2. Issues on methodology

The methods chosen in this study can have an impact on the results. First of all, the division of YA into YAM and YAA was based on a temperature threshold set at 1.0°C. Shifting this threshold up or down can have an impact on the differences found between YAM and YAA. Moreover, YAM can also be divided in two datasets. In the beginning of the melt-season, the flow is enhanced as all the snow and ice are melted in the first few warm months. The length of this event differs among the catchments as in northern catchments more snow and ice accumulate during winter compared to southern catchments. Furthermore, the length of the snowmelt season in southern catchments is longer than in northern catchments. In several years, some southern catchments did not experience a snow-accumulation season at all. In general, the average values in the YAM dataset are based on more monthly data for southern catchments than for northern catchments. The opposite for YAA is also true. Despite this bias, separating YA into YAM and YAA is useful as it reveals some important differences between the two seasons.

Second, labeling locations to the catchments is useful to extract climatic- and social-based controls. The climatic gradient was based on a yearly average temperature threshold set at 5.0°C. Shifting this threshold can have an impact on the differences found between northern and southern catchments. Examples of other climatic gradients that could be used in this study include a division between coastal and non-coastal catchments or a division based on precipitation. Each gradient would give unique results so that the results presented in this study where north and south are compared could be different if a different gradient was chosen. The east-west gradient is less arbitrary as it is based on the 'iron-curtain' and is part of the

hypothesis formulated in chapter 1. From figure 2, it is noted that southern and eastern catchments are much alike as well as northern and western catchments. This might cause some confusion in the interpretation of the results as some transition-based controls become visible in northern/southern catchments while they are also visible in western/eastern catchments. The opposite for climatic controls is also true. Although it is possible to disentangle these separate effects, it still requires careful handling of results were gradients are used. For the abovementioned reasons, it is highly recommended to look at the effect of these kinds of thresholds in future research.

Third, the two different methods used in trend analysis can influence the results presented in section 4.2. A non-seasonal Mann-Kendall trend test treats the data as a straight time-series while a seasonal Mann-Kendall trend test treats the data as a 12-month cyclical time-series where all January-values are compared and all February values etc. In general, more trends were found in MA, where the seasonal variant is used, than in YA, YAM and YAA, where the normal variant is used. One reason is that the time-series of YA, YAM and YAA have 31 data-points while MA has 372 data-points (31 January's + 31 February's etc.). The time-series of MA is much longer and weaker trends therefore have a higher chance to become significant (below the p-level of 0.05). The biggest difference between these two kinds of trend analysis is temperature. Only few trends for temperature are found in YA and YAA while in MA more than 90% of the catchments have a trend. Moreover, more trends are found for the TN load and concentrations in MA compared to the other datasets.

### 5.3. Shortcomings and future directions

In this study, several shortcomings and reliability issues on the sampling of the data exist. These issues will ultimately lead to recommendations and directions for future research.

The methods and rules used for data-collection were not uniformly applied by all countries. There is evidence that Estonia, Latvia and Russia have not followed the frequency of sampling recommended in the guidelines set by the Helsinki Commission (HELCOM, 1993). Furthermore, in some cases, time series were completed by interpolating the values whereas in other cases, a fixed ratio was used for DIN/TN and DIP/TP concentrations resulting in a 100% correlation. Sampling sites also differed among all countries in the BSDB. Some countries measured upstream of the river whereas other countries measured downstream (Stålnacke et al., 1998). Especially in the 1970s and 1980s, these issues affected the overall quality of the dataset. In the 1990s, most of these issues were solved. However, in the 1990s, still no guidelines existed for

the sampling of small rivers, on which the values of the catchments are also based (HELCOM, 1993). Although nowadays, these issues are solved, the available dataset with a time-series of 1970-2000 is possibly affected with these shortcomings.

The research presented in this study can be improved by carrying out a careful quality analysis on this dataset and remove data that are doubtful. Unfortunately, there was no time in this 20-week research to carry out such an analysis although this might greatly improve the results presented in this study.

The time-series used in this study might be too short to reveal all important effects and controls caused by the transition period. The transition period lasted until 2008 and many political and societal changes occurred in the 2000s. Therefore, not the whole story can be told in this study concerning the transition period. Although time-series until 2010 on basin level exist, due to unexpected delays of data-processing, the Baltic Nest institute does not expect to release a dataset on catchment level before 2014. It is greatly recommended to use the extended time-series in future research in order to extract the complete story concerning the transition period.
Furthermore, land-use variables were used from the year 2000. It is difficult to use land-use datasets for the BSDB as part of the BSDB lies outside Europe. Therefore, detailed European land-use datasets such as the Corine land-use dataset cannot be used solely. Furthermore, the scale and accurateness of global land-use datasets are far less than other, more regional land-use datasets so using only one global dataset is not sufficient. In this study, the Corine land-use dataset and the global land cover dataset was used. Combining different datasets is not straightforward as the classification of land-use variables is not the same in each dataset. The Baltic Nest institute only combined the two land-use datasets for the year 2000. An effort to combine the Corine dataset from 1990, 1995 and 2005 with the global land cover dataset of the same years would be helpful in determining relationships between nutrients and land-use over time.

## Chapter 6. Conclusion

The results presented in this study indicate that the controls for nitrogen and phosphorus are not the same. Therefore, improving water quality in the catchments requires different approaches. Since changes in nitrogen are very dependent on changes in cultivated area, further improving agricultural techniques that reduce nitrogen run-off should be the way forward in reducing nitrogen loads even more. Subsequently, conserving wetlands and shrubs and herbs should be prioritized as they are essential for nitrogen retention. Improving wastewater treatment plants and closing heavy polluting factories could reduce phosphorus loads to the Baltic Sea even further, especially in eastern countries. Because people in the BSDB rely on many ecosystem services that are vulnerable to eutrophication, it is important to further improve the water quality in the catchments. This is necessary to secure and sustain these services in the future.

The aim of this research was to quantify shifts and trends in water quality in terms of N and P in the BSDB and relate these shifts and trends to environmental, climatic and anthropogenic controls. Temperature increased most at the coast, probably due to warming of Baltic Sea water and reduced sea ice cover during winter. Next to a gradual increase, shifts of temperature were also observed, probably caused by NAO, which is responsible for changes in temperatures and wind-direction in the BSDB during winter in the late eighties.

When temperature is enhanced through NAO, the precipitation likely will increase. This might explain the shifts of precipitation found in the period 1981-1988. In this study, it was found that the higher the temperature change, the lower the precipitation change and vice versa (Table 4). This is in line with figure 3b, which shows that precipitation change is greater from the greater distance to the coast (were temperature change is small). Hence, in some catchments positive changes in temperature result in positive changes in precipitation (due to NAO). In other catchments there is an inverse effect.

Both temperature and precipitation influence flow as increased temperature enhance evaporation thereby decreasing the flow. Increased precipitation results in more run-off thereby increasing the flow. This explains the gradient observed in the BSDB for flow (Figure 3c). In catchments were temperature trends are present but without trends in precipitation, trends in flow are negative. In catchments were temperature trends are low and trends in precipitation are high, trends in flow are positive. The inverse effect of temperature and flow is reflected in table 4.

Negative trends for DIN and TN were most pronounced in eastern catchments. The likely candidate for these trends are changes in diffuse sources among which agricultural activities are most responsible for changes in nitrogen. Robust factor analysis revealed an area effect for N which point the cause of trends in nitrogen to changes in land-use. Furthermore, the fact that cultivated and artificial area are strongly correlated with DIN and TN confirm this land-use based control even more (Table 7). The inverse correlation with wetlands confirms that wetlands are important for nitrogen retention. Moreover, expansion of cultivated and artificial areas resulted in a reduction in the area of wetlands and shrubs/herbs. The fact that no clear spatial pattern was found for the shifts of DIN and TN suggest that the transition period resulted not in sudden reduction in DIN and TN. Changes in nitrogen were more gradual rather than sudden.

The opposite pattern of trends for DIP and TP were observed when compared to the pattern of trends for nitrogen. In eastern catchments, trends in phosphorus are positive, while in western catchments, trends are negative. From 1975, more advanced wastewater treatment techniques, closure of polluting factories and an increased use of phosphorus-free detergents resulted in reductions in phosphorus originating from point-sources. These improvements are the result of societal changes leading to more public awareness, improvements of technologies, and close collaboration among countries due to efforts of HELCOM. In eastern countries, these societal changes were hindered by the iron curtain. During the transition period in eastern countries, improvements in point-sources were applied but many occurred in the 2000s which makes it impossible to isolate these, transition-based changes. Gradual changes in the 1970s result in positive trends in eastern catchments and hence explain the strong gradient between west and east for phosphorus.

**References**

Ærtebjerg, G., J.H. Andersen & O.S. Hansen. (2003), Nutrients and eutrophication in danish marine waters. A challenge for science and management. National Environmental Research Institute, pp.1-126.

Alheit, J., T. Pohlmann, M. Casini et al. (2012), Climate variability drives anchovies and sardines into the north and baltic seas. Progress in oceanography 96, pp.128-139.

Arheimer, B. & R. Lidén. (2000), Nitrogen and phosphorus concentrations from agricultural catchments—influence of spatial and temporal variable. Journal of Hydrology 227, pp.140-159.

Baltic Nest Institute (BNI). (2013), Http://www.balticnest.org/.

Bengtsson, L. (1995), Baltic sea experiment BALTEX: Initial implementation plan. International Baltex Secretariat 2, pp.1-84.

Boesch, D., R. Hecky, C. O'Melia et al. (2006), Eutrophication of swedish seas. Swedish Environmental Protection Agency Stockholm, pp.5509.

Boesch, D., R. Hecky, C. O'Melia et al. (2008), Eutrophication of seas along Sweden's westcoast. Swedish Environmental Protection Agency Stockholm, pp.5898.

Bowes, M.J., J.T. Smith, C. Neal et al. (2009), Changes in water quality of the river frome (UK) from 1965 to 2009: Is phosphorus mitigation finally working? Science of the total environment 409, pp.3418-3430.

Carstensen, J., D.J. Conley, J.H. Andersen et al. (2006), Coastal eutrophication and trend reversal: A danish case study. Limnology and Oceanography 51, pp.398-408.

Conley, D.J., S. Björck, E. Bonsdorff et al. (2009), Hypoxia-related processes in the baltic sea. Environmental Science & Technology 43, pp.3412-3420.

Cuo, L., D.P. Lettenmaier, M. Alberti et al. (2009), Effects of a century of land cover and climate change on the hydrology of puget sound basin. Hydrological processes 23, pp.907-933.

Diaz, R. & R. Rosenberg. (2008), Spreading dead zones and consequences for marine ecosystems. Science 321, pp.926-929.

Feistel, R., G. Nausch, T. Heene et al. (2004), Evidence for a warm water inflow into the baltic proper in summer 2003. Oceanologia 46, pp.581-598.

Food and Agricultural Organization (FAO). (2012), Current world fertilizer trends and outlook to 2016. Rome

Galloway, J.N., J.D. Aber, J.W. Erisman et al. (2003), The nitrogen cascade. Bioscience 53, pp.341-356.

Graham, L.P. & S. Bergström. (2001), Water balance modelling in the baltic sea drainage basin - analysis of meteorological and hydrological approaches. Meteorology, Atmosphere, Physics 77, pp.45-60.

Hägg, H.E., S.W. Lyon, T. Wällstedt, C.M. Mörth, B. Claremar, C Humborg. (submitted), Future nutrient load scenarios for the Baltic Sea due to climate and lifestyle changes.

Hamed, K.H. (2009), Exact distribution of the Mann–Kendall trend test statistic for persistent data. Journal of Hydrology 365, pp.86-94.

Hannerz, F, G. Destouni. (2006), Spatial characterization of the baltic sea drainage basin and its unmonitored catchments. Ambio 35, pp.214-219.

Haylock, M.R., N. Hofstra, A.M.G. Klein-Tank et al. (2008), A european daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. Journal of Geophysical Research 113, pp.1-12.

HELCOM. (2007), Climate change in the baltic sea area. Baltic Sea Environment Proceedings 111.

HELCOM. (2011), Fifth Baltic sea pollution load compilation (PLC-5). Baltic Sea Environment Proceedings 128, pp.1-401.

Herman, A., J. Jedrasik & M. Kowalewski. (2011), Numerical modelling of thermodynamics and dynamics of sea ice in the baltic sea. Ocean Science 7, pp.257-276.

Hipel, K.W. & A.I. McLeod. (1994), Time series modelling of water resources and Environmental Systems. chapter 23: Nonparametric tests for trend detection. Elsevier, Amsterdam, pp. 853-938.

Hurrel, J.W. (1995), Decadal trends in the north Atlantic oscillation regional temperatures and precipitation. Science 269, pp.676-679.

Hussian, M., A. Grimvall & W. Petersen. (2005), Estimation of the human impact on nutrient loads carried by the elbe river. Environmental monitoring assessment 96, pp.15-33.

Iital, A., P. Stålnacke, J. Deelstra et al. (2005), Effects of large-scale changes in emissions on nutrient concentrations in estonian rivers in the lake peipsi drainage basin. Journal of Hydrology 304, pp.261-273.

Jansson, Å., C. Folke & S. Langaas. (1998), Quantifying the nitrogen retention capacity of natural wetlands in the large-scale drainage basin of the Baltic Sea. Landscape Ecology 13, pp.249-262.

Kotta, J., I. Kotta, M. Simm et al. (2009), Separate and interactive effects of eutrophication and climate variables on the ecosystem elements of the gulf of riga. Estuarine, Coastal and Shelf Science 84, pp.509-518.

Krause, S., J. Jacobs, A. Voss et al. (2008), Assessing the impact of changes in landuse and management practices on the diffuse pollution and retention of nitrate in a riparian floodplain. Science of the total environment 389, pp.149-164.

Lin, Y.P., N.M. Hong, P.J. Wu et al. (2007), Modelling and assessing land-use and hydrological processes to future land-use and climate change in watershed land-use planning. Environmental Geology 53, pp.623-634.

Lyon, S.W., H. Laudon, J. Seibert et al. (2010), Controls on snowmelt water mean transit times in northern boreal catchments. Hydrological processes 21, pp.1672-1684.

Lyon, S.W., M. Nathanson, A. Spans et al. (2012), Specific discharge variability in a boreal landscape. Water Resour. Res. 48

Matthäus, W. & H. Schinke. (1999), The influence of river runoff on deep water conditions of the baltic sea. Hydrobiologia 393, pp.1-10.

Meier, H.E.M., K. Eilola & E. Almroth. (2011), Climate-related changes in marine ecosystems simulated with a 3-dimensional coupled physical-biogeochemical model of the baltic sea. Climate Research 48, pp.31-55.

Meier, H.E.M., R. Hordoir, H.C. Andersson et al. (2012), Modeling the combined impact of changing climate and changing nutrient loads on the baltic sea environment in an ensemble of transient simulations for 1961–2099. Climate Dynamics 39, pp.2421-2441.

Moore, K., D. Pierson, K. Pettersson et al. (2008), Effects of warmer world scenarios on hydrologic inputs to lake malaren, sweden and implications for nutrient loads. Hydrobiologia 599, pp.191-199.

Nausch, G., D. Nehring & G. Aertebjerg. (1999), Anthropogenic nutrient load of the baltic sea. Limnologica 29, pp.233-241.

Nausch, G., W. Matthäus & R. Feistel. (2003), Hydrographic and hydrochemical conditions in the gotland deep area between 1992 and 2003.. Oceanologia 45, pp.557.

Neumann, T. (2010), Climate-change effects on the baltic sea ecosystem: A model study.. Journal of marine systems 81, pp.213-224.

Österblom, H., S. Hansson, U. Larsson et al. (2007), Human-induced trophic cascades and ecological regime shifts in the baltic sea. Ecosystems 10, pp.877-889.

Pastuzak, M. & J. Igras. (2012a), Temporal and spatial differences in emission of nitrogen and phosphorus from polish territory to the baltic sea. National Marine Fisheries Research Institute, Gdynia - Puławy.

Pastuzak, M., P. Stålnacke, K. Pawlikowski et al. (2012b), Response of polish rivers (vistula, oder) to reduced pressure from point sources and agriculture during the transition period (1988–2008). Journal of Marine Systems 94, pp.157-173.

Pawlak, J.F., M.M. Laamanen & J.H. Andersen. (2009), Eutrophication in the baltic sea: An integrated thematic assessment of the effects of nutrient enrichment in the baltic sea region,executive summary. Helsinki Commission Helsinki, pp.115A.

Reckermann, M., J. Langner, A. Omstedt et al. (2011), BALTEX - an interdisciplinary research network for the baltic sea region. Environmental Research Letters 6

Richardson, C.J., S. Qian, S.B. Craft et al. (1997), Predictive models for phosphorus retention in wetlands. Wetlands Ecology and Management 4, pp.159-175.

Kjellström, E., K., Ruosteenoja. (2007). Present-day and future precipitation in the Baltic Sea region as simulated in a suite of regional climate models. Climatic Change 81, pp.281-291.

Savchuk, O.P., F. Wulff, S. Hille et al. (2008), The baltic sea a century ago - a reconstruction from model simulations, verified by observations.. Journal of Marine Systems 74, pp.485-494.

Schernewski, G. & T. Neumann. (2005), The trophic state of the baltic sea a century ago: A model simulation study. Journal of Marine Systems 53, pp.109-124.

Schimanke, S., H.E.M. Meier, E. Kjellstrom et al. (2012), The climate in the Baltic sea region during the last millennium. Climate past discussions 8, pp.1369-1407.

Sellner, K.G., G.J. Doucette & G.J. Kirkpatrick. (2003), Harmful algal blooms: Causes, impacts and detection. J. Ind. Microbiology and Biotechnology 30, pp.383-406.

Smith, S.V., D.P. Swaney & L. Talaue-McManus. (2003), Humans, hydrology, and the distribution of inorganic nutrient loading to the ocean.. BioScience 53, pp.235-246.

Smith, S.V., F. Hannerz, D.P. Swaney et al. (2005), River nutrient loads and catchment size. Biogeochemistry 75, pp.83-107.

Sörlin, T. (1982), The gulf of bothnia: The northernmost part of the Baltic sea. Aquatic Ecology 16, pp.287-288.

Stålnacke, P., A. Grimvall, K. Sundblad et al. (1998), Estimation of riverine load of nitrogen and phosphorus to the baltic sea, 1970-1993. Environmental Monitoring and Assessment 58, pp.173-200.

Taylor, W.A. (2000), Change-point analyzer 2.0 shareware program. Taylor Enterprises, Libertyville, Illinois, Web: http://www.variation.com/cpa.

Temnerud, J., J. Seibert, M. Jansson et al. (2007), Spatial variation in discharge and concentrations of organic carbon in a catchment network of boreal streams in northern Sweden. Journal of Hydrology 342, pp.72-87.

Teutschbein, C. & J. Seibert. (2010), Regional climate models for hydrological impact studies at the catchment scale: A review of recent modeling strategies. Geography Compass 4, pp.1-7.

Thorborg, M. (2012), Demographic development in the baltic sea region. The Rural Society Chapter 8, pp.103-116.

Trenberth, K.E., P.D. jones, P. ambenje, R. bojariu, D. easterling, A. klein tank, D. parker, F. rahimzadeh, J.A. renwick, M. rusticucci, B. soden and P. zhai, 2007: Observations: Surface and atmospheric climate change. in: Climate change 2007: The physical science basis. contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change [solomon, S., D. qin, M. manning, Z. chen, M. marquis, K.B. averyt, M. tignor and H.L. miller (eds.)]. cambridge university press, cambridge, united kingdom and new york, NY, USA.

Todd, D.C.E., A.M. Goss, D. Tripathy et al. (2007), The effects of landscape transformation in a changing climate on local water resources. Physical geography 28, pp.21-36.

Väänänen, R. (2008), Phosphorus retention in forest soils and the functioning of buffer zones used in forestry. Academic dissertation, pp.11,30.

Van der Velde, Y., S.W. Lyon & G. Destouni. (2013), Data-driven regionalization of river discharges and emergent land cover-evapotranspiration relationships across sweden. Journal of Geophysical Research

Voss, M., J.W. Dippner, C. Humborg et al. (2011), History and scenarios of future development of baltic sea eutrophication. Estuarine, Coastal and Shelf Science 92, pp.307-322.

Wilson, D., H. Hisdal & D. Lawrence. (2010), Has streamflow changed in the nordic countries? – recent trends and comparisons to hydrological projections. Journal of Hydrology 394, pp.334-346.

Wright, R.F. (1998), Effect of increased carbon dioxide and temperature on runoff chemistry at a forested catchment in southern norway (CLIMEX project). Ecosystems 1, pp.216-225.

Wulff, F., E. Bonsdorff, I.-. Gren et al. (2001), Giving advice on cost effective measures for a cleaner baltic sea: A challenge for science. Ambio 30, pp.254-259.

## Appendix A.1

## R-script non-seasonal Mann Kendall trend test

```
Data-file <- read.csv("C:/R/Thesis Mann-Kendall/file-name", sep=",",header=T)
require(Kendall)
Kcolumns<-c("insert variables")
test <-sapply(Kcolumns,FUN=function(x)MannKendall(file-name[,x]))
write.table(test,file="C:/R/Thesis Mann-Kendall/file-name.csv",sep=";")
```

## R-Script seasonal Mann-Kendall trend test

```
Data-file <- read.csv("C:/R/Thesis Mann-Kendall/file-name", sep=",",header=T)
require(Kendall)
Kcolumns<-c("insert variables")
test <-sapply(Kcolumns,FUN=function(x)SeasonalMannKendall(ts(file-name[,x]), start=1970,
end=2000, frequency =12)) write.table (test,file="C:/R/Thesis Mann-Kendall/file-
name.csv",sep=";")
```

## Appendix A.2

## R-script Shift-point analysis

```
calcswitch<-function(datacc,xvalcnc,row,swpl){
  ##plots generated data
  if(swpl>0){
    par(mfg=c(row,1))
    lines(xvalcnc,abs(cumsum(datacc-mean(datacc))/length(datacc)))
    ##plots original data
  }
  amx<-max(abs(cumsum(datacc-mean(datacc))))
  ##switchpoint is timevalue with amx
  switchp<-xvalcnc[abs(cumsum(datacc-mean(datacc)))==amx]
  ##both maxdif and maxp can indicate a switchpoint
  ##maxdif is the maximum difference of the cumsum(corv[sel]-mean(corv[sel])
  maxdif<-(max(cumsum(datacc-mean(datacc)))-min(cumsum(datacc-mean(datacc))))/length(xvalcnc)
  if(swpl==0)maxp<-amx
  if(swpl>0)maxp<-abs(cumsum(datacc-mean(datacc)))[xvalcnc==swpl]
  maxp<-maxp/length(xvalcnc)
  return(c(switchp,maxdif,maxp))
}
##tests if switchpoint is significant
findswitch<-function(xdata,bdata){
  try(dev.off())
  ##detrend data
  bdatadt<-bdata+coef(lm(bdata~xdata))[2]*(xdata-mean(xdata))
  ##fit arma model to data
  armodel <-auto.arima(scale(bdatadt),d=0,max.Q=0,max.P=0,ic="bic",stepwise=F)
  arc<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ar"]
  mac<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ma"]
  ##generate nr surrogate timeseries with this timeseries model
  ## if there is significant autocorrelation create nr surrogate timeseries using the arma
model
  if(length(arc)+length(mac)>0)databoot<-
sapply(rep(1,nr),FUN=function(x)arima.sim(n=length(xdata),list(ar = arc, ma = mac)))
  ## if there is not significant autocorrelation bootstrap existing data
  if(length(arc)+length(mac)==0)databoot<-
sapply(rep(1,nr),FUN=function(x)sample(scale(bdatadt),length(bdatadt),replace=F))
  xvalcn<-as.numeric(xdata)
  datac<-as.numeric(scale(bdatadt))
  rangen<-c(min(xvalcn),max(xvalcn))
  swp<-matrix(ncol=2,nrow=7)
  ##find and plot first switchpoint
  par(mfcol=c(8,1))
  par(mar=c(2,2,2,1))
  par(mfg=c(1,1))
  plot(xvalcn,datac,xlim=c(min(xvalcn),max(xvalcn)),typ="l",lwd=1,xlab="",ylab="",col=1)
  rangen<-c(min(xvalcn),max(xvalcn))
  sel<-xvalcn>=rangen[1]&xvalcn<=rangen[2]
  par(mfg=c(2,1))
  plot(xvalcn,abs(cumsum(datac-
mean(datac))/length(datac)),xlim=c(min(xvalcn),max(xvalcn)),ylim=c(0,0.5),typ="l",lwd=1,xlab="
",ylab="",col=2)
  swdat<-calcswitch(datac,xvalcn,2,0)
  swboot<-apply(databoot,2,FUN=function(x)calcswitch(x,xvalcn,2,swdat[1]))
  lines(xvalcn,abs(cumsum(datac-mean(datac))/length(datac)),col=2,lwd=2)
  tst <- (swdat[1]>rangen[1]+0.1*(rangen[2]-rangen[1]))&(swdat[1]<rangen[2]-0.1*(rangen[2]-
rangen[1]))&swdat[1]-rangen[1]>2&rangen[2]-swdat[1]>2
  ##here we test for significance: if maxdif or maxp from calcswitch is significant, switch
point is significant, unless it is too close to the edges
  if((quantile(swboot[3,],sign)<swdat[3]|quantile(swboot[2,],sign)<swdat[2])&tst){
    swp[1,1]<-swdat[1]
    par(mfg=c(1,1))
    lines(c(swp[1,1],swp[1,1]),c(0,max(datac)),col=3,lwd=4)
    par(mfg=c(2,1))
    lines(c(swp[1,1],swp[1,1]),c(0,0.5),col=3,lwd=4)
    swp[1,2]<-1-sum(swboot[3,]>swdat[3])/nr
  }
  if(!is.na(swp[1,1])){
    rangen<-c(min(xvalcn),swp[1,1])
    sel<-xvalcn>=rangen[1]&xvalcn<=rangen[2]
    armodel <-auto.arima(scale(bdatadt[sel]),d=0,max.Q=0,max.P=0,ic="bic",stepwise=F)
```

```
    arc<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ar"]
    mac<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ma"]
    ##generate nr surrogate timeseries with this timeseries model
    ## if there is significant autocorrelation create nr surrogate timeseries using the arma
model
    if(length(arc)+length(mac)>0)databoot<-
sapply(rep(1,nr),FUN=function(x)arima.sim(n=length(xdata[sel]),list(ar = arc, ma = mac)))
    ## if there is not significant autocorrelation bootsrap existing data
    if(length(arc)+length(mac)==0)databoot<-
sapply(rep(1,nr),FUN=function(x)sample(scale(bdatadt[sel]),length(bdatadt[sel]),replace=F))
    par(mfg=c(3,1))
    plot(xvalcn[sel],abs(cumsum(datac[sel]-
mean(datac[sel]))/length(datac[sel])),xlim=c(min(xvalcn),max(xvalcn)),ylim=c(0,0.5),typ="l",lw
d=1,xlab="",ylab="",col=2)
    swdat<-calcswitch(datac[sel],xvalcn[sel],1,0)
    swboot<-apply(databoot,2,FUN=function(x)calcswitch(x,xvalcn[sel],3,swdat[1]))
    lines(xvalcn[sel],abs(cumsum(datac[sel]-mean(datac[sel]))/length(datac[sel])),col=2,lwd=2)
    tst <- (swdat[1]>rangen[1]+0.1*(rangen[2]-rangen[1]))&(swdat[1]<rangen[2]-0.1*(rangen[2]-
rangen[1]))&swdat[1]-rangen[1]>2&rangen[2]-swdat[1]>2
    if((quantile(swboot[3,],sign)<swdat[3]|quantile(swboot[2,],sign)<swdat[2])&tst){
      ##if significant plot switchpoint and save results
      swp[2,1]<-swdat[1]
      par(mfg=c(1,1))
      lines(c(swp[2,1],swp[2,1]),c(0,max(datac)),col=3,lwd=4)
      par(mfg=c(3,1))
      lines(c(swp[2,1],swp[2,1]),c(0,0.5),col=3,lwd=4)
      swp[2,2]<-1-sum(swboot[3,]>swdat[3])/nr
    }
    ##If we found 1 significant switchpoint, we test both sides of the switchpoint for another
significant switchpoint
    rangen<-c(swp[1,1],max(xvalcn))
    sel<-xvalcn>=rangen[1]&xvalcn<=rangen[2]
    armodel <-auto.arima(scale(bdatadt[sel]),d=0,max.Q=0,max.P=0,ic="bic",stepwise=F)
    arc<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ar"]
    mac<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ma"]
    ##generate nr surrogate timeseries with this timeseries model
    ## if there is significant autocorrelation create nr surrogate timeseries using the arma
model
    if(length(arc)+length(mac)>0)databoot<-
sapply(rep(1,nr),FUN=function(x)arima.sim(n=length(xdata[sel]),list(ar = arc, ma = mac)))
    ## if there is not significant autocorrelation bootsrap existing data
    if(length(arc)+length(mac)==0)databoot<-
sapply(rep(1,nr),FUN=function(x)sample(scale(bdatadt[sel]),length(bdatadt[sel]),replace=F))
    par(mfg=c(4,1))
    plot(xvalcn[sel],abs(cumsum(datac[sel]-
mean(datac[sel]))/length(datac[sel])),xlim=c(min(xvalcn),max(xvalcn)),ylim=c(0,0.5),typ="l",lw
d=1,xlab="",ylab="",col=2)
    swdat<-calcswitch(datac[sel],xvalcn[sel],1,0)
    swboot<-apply(databoot,2,FUN=function(x)calcswitch(x,xvalcn[sel],4,swdat[1]))
    lines(xvalcn[sel],abs(cumsum(datac[sel]-mean(datac[sel]))/length(datac[sel])),col=2,lwd=2)
    tst <- (swdat[1]>rangen[1]+0.1*(rangen[2]-rangen[1]))&(swdat[1]<rangen[2]-0.1*(rangen[2]-
rangen[1]))&swdat[1]-rangen[1]>2&rangen[2]-swdat[1]>2
    if((quantile(swboot[3,],sign)<swdat[3]|quantile(swboot[2,],sign)<swdat[2])&tst){
      swp[3,1]<-swdat[1]
      par(mfg=c(1,1))
      lines(c(swp[3,1],swp[3,1]),c(0,max(datac)),col=3,lwd=4)
      par(mfg=c(4,1))
      lines(c(swp[3,1],swp[3,1]),c(0,0.5),col=3,lwd=4)
      swp[3,2]<-1-sum(swboot[3,]>swdat[3])/nr
    }
  }
  if(!is.na(swp[2,1])){
    rangen<-c(min(xvalcn),swp[2,1])
    sel<-xvalcn>=rangen[1]&xvalcn<=rangen[2]
    armodel <-auto.arima(scale(bdatadt[sel]),d=0,max.Q=0,max.P=0,ic="bic",stepwise=F)
    arc<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ar"]
    mac<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ma"]
    ##generate nr surrogate timeseries with this timeseries model
    ## if there is significant autocorrelation create nr surrogate timeseries using the arma
model
    if(length(arc)+length(mac)>0)databoot<-
sapply(rep(1,nr),FUN=function(x)arima.sim(n=length(xdata[sel]),list(ar = arc, ma = mac)))
    ## if there is not significant autocorrelation bootsrap existing data
    if(length(arc)+length(mac)==0)databoot<-
sapply(rep(1,nr),FUN=function(x)sample(scale(bdatadt[sel]),length(bdatadt[sel]),replace=F))
```

```
    par(mfg=c(5,1))
    plot(xvalcn[sel],abs(cumsum(datac[sel]-
mean(datac[sel]))/length(datac[sel])),xlim=c(min(xvalcn),max(xvalcn)),ylim=c(0,0.5),typ="l",lw
d=1,xlab="",ylab="",col=2)
    swdat<-calcswitch(datac[sel],xvalcn[sel],5,0)
    swboot<-apply(databoot,2,FUN=function(x)calcswitch(x,xvalcn[sel],5,swdat[1]))
    lines(xvalcn[sel],abs(cumsum(datac[sel]-mean(datac[sel]))/length(datac[sel])),col=2,lwd=2)
    tst <- (swdat[1]>rangen[1]+0.1*(rangen[2]-rangen[1]))&(swdat[1]<rangen[2]-0.1*(rangen[2]-
rangen[1]))&swdat[1]-rangen[1]>2&rangen[2]-swdat[1]>2
    if((quantile(swboot[3,],sign)<swdat[3]|quantile(swboot[2,],sign)<swdat[2])&tst){
      swp[4,1]<-swdat[1]
      par(mfg=c(1,1))
      lines(c(swp[4,1],swp[4,1]),c(0,max(datac)),col=3,lwd=4)
      par(mfg=c(5,1))
      lines(c(swp[4,1],swp[4,1]),c(0,0.5),col=3,lwd=4)
      swp[4,2]<-1-sum(swboot[3,]>swdat[3])/nr
    }
    rangen<-c(swp[2,1],swp[1,1])
    sel<-xvalcn>=rangen[1]&xvalcn<=rangen[2]
    armodel <-auto.arima(scale(bdatadt[sel]),d=0,max.Q=0,max.P=0,ic="bic",stepwise=F)
    arc<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ar"]
    mac<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ma"]
    ##generate nr surrogate timeseries with this timeseries model
    ## if there is significant autocorrelation create nr surrogate timeseries using the arma
model
    if(length(arc)+length(mac)>0)databoot<-
sapply(rep(1,nr),FUN=function(x)arima.sim(n=length(xdata[sel]),list(ar = arc, ma = mac)))
    ## if there is not significant autocorrelation bootsrap existing data
    if(length(arc)+length(mac)==0)databoot<-
sapply(rep(1,nr),FUN=function(x)sample(scale(bdatadt[sel]),length(bdatadt[sel]),replace=F))
    par(mfg=c(6,1))
    plot(xvalcn[sel],abs(cumsum(datac[sel]-
mean(datac[sel]))/length(datac[sel])),xlim=c(min(xvalcn),max(xvalcn)),ylim=c(0,0.5),typ="l",lw
d=1,xlab="",ylab="",col=2)
    swdat<-calcswitch(datac[sel],xvalcn[sel],6,0)
    swboot<-apply(databoot,2,FUN=function(x)calcswitch(x,xvalcn[sel],6,swdat[1]))
    lines(xvalcn[sel],abs(cumsum(datac[sel]-mean(datac[sel]))/length(datac[sel])),col=2,lwd=2)
    tst <- (swdat[1]>rangen[1]+0.1*(rangen[2]-rangen[1]))&(swdat[1]<rangen[2]-0.1*(rangen[2]-
rangen[1]))&swdat[1]-rangen[1]>2&rangen[2]-swdat[1]>2
    if((quantile(swboot[3,],sign)<swdat[3]|quantile(swboot[2,],sign)<swdat[2])&tst){
      swp[5,1]<-swdat[1]
      par(mfg=c(1,1))
      lines(c(swp[5,1],swp[5,1]),c(0,max(datac)),col=3,lwd=4)
      par(mfg=c(6,1))
      lines(c(swp[5,1],swp[5,1]),c(0,0.5),col=3,lwd=4)
      swp[5,2]<-1-sum(swboot[3,]>swdat[3])/nr
    }
  }
  if(!is.na(swp[3,1])){
    rangen<-c(swp[1,1],swp[3,1])
    sel<-xvalcn>=rangen[1]&xvalcn<=rangen[2]
    armodel <-auto.arima(scale(bdatadt[sel]),d=0,max.Q=0,max.P=0,ic="bic",stepwise=F)
    arc<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ar"]
    mac<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ma"]
    ##generate nr surrogate timeseries with this timeseries model
    ## if there is significant autocorrelation create nr surrogate timeseries using the arma
model
    if(length(arc)+length(mac)>0)databoot<-
sapply(rep(1,nr),FUN=function(x)arima.sim(n=length(xdata[sel]),list(ar = arc, ma = mac)))
    ## if there is not significant autocorrelation bootsrap existing data
    if(length(arc)+length(mac)==0)databoot<-
sapply(rep(1,nr),FUN=function(x)sample(scale(bdatadt[sel]),length(bdatadt[sel]),replace=F))

    par(mfg=c(7,1))
    plot(xvalcn[sel],abs(cumsum(datac[sel]-
mean(datac[sel]))/length(datac[sel])),xlim=c(min(xvalcn),max(xvalcn)),ylim=c(0,0.5),typ="l",lw
d=1,xlab="",ylab="",col=2)
    swdat<-calcswitch(datac[sel],xvalcn[sel],7,0)
    swboot<-apply(databoot,2,FUN=function(x)calcswitch(x,xvalcn[sel],7,swdat[1]))
    lines(xvalcn[sel],abs(cumsum(datac[sel]-mean(datac[sel]))/length(datac[sel])),col=2,lwd=2)
    tst <- (swdat[1]>rangen[1]+0.1*(rangen[2]-rangen[1]))&(swdat[1]<rangen[2]-0.1*(rangen[2]-
rangen[1]))&swdat[1]-rangen[1]>2&rangen[2]-swdat[1]>2
    if((quantile(swboot[3,],sign)<swdat[3]|quantile(swboot[2,],sign)<swdat[2])&tst){
      swp[6,1]<-swdat[1]
      par(mfg=c(1,1))
```

```
      lines(c(swp[6,1],swp[6,1]),c(0,max(datac)),col=3,lwd=4)
      par(mfg=c(7,1))
      lines(c(swp[6,1],swp[6,1]),c(0,0.5),col=3,lwd=4)
      swp[6,2]<-1-sum(swboot[3,]>swdat[3])/nr
    }
    rangen<-c(swp[3,1],max(xvalcn))
    sel<-xvalcn>=rangen[1]&xvalcn<=rangen[2]
    armodel <-auto.arima(scale(bdatadt[sel]),d=0,max.Q=0,max.P=0,ic="bic",stepwise=F)
    arc<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ar"]
    mac<-coef(armodel)[substr(names(coef(armodel)),1,2)=="ma"]
    ##generate nr surrogate timeseries with this timeseries model
    ## if there is significant autocorrelation create nr surrogate timeseries using the arma
model
    if(length(arc)+length(mac)>0)databoot<-
sapply(rep(1,nr),FUN=function(x)arima.sim(n=length(xdata[sel]),list(ar = arc, ma = mac)))
    ## if there is not significant autocorrelation bootsrap existing data
    if(length(arc)+length(mac)==0)databoot<-
sapply(rep(1,nr),FUN=function(x)sample(scale(bdatadt[sel]),length(bdatadt[sel]),replace=F))
    par(mfg=c(8,1))
    plot(xvalcn[sel],abs(cumsum(datac[sel]-
mean(datac[sel]))/length(datac[sel])),xlim=c(min(xvalcn),max(xvalcn)),ylim=c(0,0.5),typ="l",lw
d=1,xlab="",ylab="",col=2)
    swdat<-calcswitch(datac[sel],xvalcn[sel],8,0)
    swboot<-apply(databoot,2,FUN=function(x)calcswitch(x,xvalcn[sel],8,swdat[1]))
    lines(xvalcn[sel],abs(cumsum(datac[sel]-mean(datac[sel]))/length(datac[sel])),col=2,lwd=2)
    tst <- (swdat[1]>rangen[1]+0.1*(rangen[2]-rangen[1]))&(swdat[1]<rangen[2]-0.1*(rangen[2]-
rangen[1]))&swdat[1]-rangen[1]>2&rangen[2]-swdat[1]>2
    if((quantile(swboot[3,],sign)<swdat[3]|quantile(swboot[2,],sign)<swdat[2])&tst){
      swp[7,1]<-swdat[1]
      par(mfg=c(1,1))
      lines(c(swp[7,1],swp[7,1]),c(0,max(datac)),col=3,lwd=4)
      par(mfg=c(8,1))
      lines(c(swp[7,1],swp[7,1]),c(0,0.5),col=3,lwd=4)
      swp[7,2]<-1-sum(swboot[3,]>swdat[3])/nr
    }
  }
  if(sum(!is.na(swp))>0)return(matrix(swp[!is.na(swp[,1]),],ncol=2))
  if(sum(!is.na(swp))==0)return(0)
}
############ Program
require(forecast)
##number of surrogate timeseries to test for significance
nr<-3256
##read data for 1 catchment
watershed <- YA.bulk[,2]=='151' ###OF return.data <- input.YA.1
return.data <- ts(YA.bulk[watershed,]) ###OF return.data <- input.YA.1
##significance level to test for switchpoint sign
sign<-0.95
1],x))
write.table(file="test.csv",sep=";",
 sapply(tst,FUN=function(x){
 tf<-rep(NA,7)
 if(length(as.vector(x))>1)tf[1:length(x[,1])]<-x[,1]
 return(tf)
 }))
```

## Appendix A.3

## R-script Extension Switch-point analysis

```
d<-dim(YA.bulk2) #get dimensions of matrix data-file
require(gtools)
watershed<-unique(unlist(YA.bulk2[,2])) #unique list of watersheds
csvlist<-mixedsort(list.files(pattern="*.csv")) #list of shift in watershed
for (k in seq(along=watershed)){
  #check each line in data-file to match watershed id
  m = matrix(0,7,33) #make matrix of zeros to hold output
  Switch<-read.table(csvlist[k],sep=",",header=T) #load switch file
  fout=csvlist[k] #get output file name
  for (q in 1:d[1]){ #use dimension in data-file
    if (YA.bulk2[q,2] == watershed[k]) {# Loops through and does a 3 year mean based on switch
      for(j in seq(along=Switch[1,])){ #cols in switch
        for(i in seq(along=Switch[,1])){#rows in switch
          Year<-Switch[i,j] #get year for analysis from switch
          if(is.na(Year))Year<-0
            if(YA.bulk2[q,1] == Year){ #if the yr in data-file=year in switch, do the math
              startyr<-YA.bulk2[q,j+1] #change columns for every iteration (new variable)
              endyr<-YA.bulk2[q+3,j+1] #End year add 3
              change <- (endyr-startyr)/3 #math
              m[i,j-1]=change #add value to matrix, dims are same as switch
            }
        }
      }
      write.csv(m,paste("out_",fout))
    }
  }
}
```

## Appendix A.4

## R-script Robust factor analysis

```
library(StatDA)
sel=c("Variables")
x=(YAA.Zt[,sel])
# construct orthonormal basis: (matrix with 31 rows and 30 columns)
V=matrix(0,nrow=ncol(x),ncol=ncol(x)-1)
for (i in 1:ncol(V)){
  V[1:i,i] <- 1/i
  V[i+1,i] <- (-1)
  V[,i] <- V[,i]*sqrt(i/(i+1))
}
# robust scaling
x.rsc=scale(log10(x),x.mcd$cent,sqrt(diag(x.mcd$cov)))
# robust PFA
res5R=pfa(x.rsc,factors=3,covmat=x.mcd,scores="regression",rotation="varimax")
rownames(res5R$loa)=rownames(res5$loa)

#loadings plots
png('datafile'.png', width=2000, height=1000,pointsize=35)
loadplot(res5Rlogcentr,titlepl="Robust FA (clr-transformed)", crit=0.1)
dev.off()
#Factor Matrix
write.csv(res5Rlogcentr$loa,"data-file.csv")
```

## Appendix B.1

## General characteristics of the dataset separated by region

**Table B.1.1.** Minimum, maximum, median and mean for all variables for the yearly average (YA), the yearly average in the snowmelt season (YAM) and the yearly average in the snow accumulation season (YAA) for northern catchments and southern catchments.

| | | Minimum | | | Maximum | | | Median | | | Mean | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Unit** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** |
| | | **North** | | | | | | | | | | | |
| **Temperature** | **°C** | -4.2 | 5.8 | -14.8 | 7.0 | 13.0 | 0.3 | 2.6 | 9.6 | -5.5 | 2.4 | 9.6 | -5.7 |
| **Precipitation** | **mm/month** | 27 | 26 | 19 | 82 | 98 | 90 | 48 | 56 | 38 | 48 | 56 | 39 |
| **Flow** | **mm/month** | 4 | 2 | 1 | 115 | 137 | 131 | 26 | 32 | 20 | 29 | 35 | 23 |
| **DIN** | **mg/ m²/month** | 0.6 | 0.6 | 0.3 | 200 | 220 | 259 | 6 | 6 | 6 | 15 | 15 | 16 |
| **DIN** | **mg/L** | 0.03 | 0.01 | 0.01 | 5 | 7 | 7 | 0.3 | 0.3 | 0.3 | 0.6 | 0.6 | 0.6 |
| **TN** | **mg/ m²/month** | 3.1 | 1.1 | 1.5 | 253 | 307 | 339 | 18 | 23 | 14 | 29 | 32 | 26 |
| **TN** | **mg/L** | 0.13 | 0.03 | 0.06 | 7 | 10 | 10 | 0.8 | 0.9 | 0.6 | 1.1 | 1.2 | 1.0 |
| **DIP** | **mg/ m²/month** | 0.005 | 0.02 | 0.01 | 6 | 7 | 7 | 0.3 | 0.4 | 0.2 | 0.7 | 0.8 | 0.6 |
| **DIP** | **mg/L** | 0.001 | 0.001 | 0.001 | 0.2 | 0.3 | 0.3 | 0.01 | 0.02 | 0.01 | 0.03 | 0.03 | 0.02 |
| **TP** | **mg/ m²/month** | 0.1 | 0.08 | 0.07 | 17 | 25 | 11 | 1.0 | 1.3 | 0.6 | 1.6 | 1.9 | 1.2 |
| **TP** | **mg/L** | 0.01 | 0.01 | 0.003 | 0.4 | 0.5 | 0.5 | 0.04 | 0.05 | 0.03 | 0.06 | 0.07 | 0.05 |
| | | **South** | | | | | | | | | | | |
| **Temperature** | **°C** | -0.3 | 7.2 | -10.4 | 10.2 | 13.5 | 1.0 | 6.9 | 9.9 | -1.9 | 6.8 | 10.0 | -2.2 |
| **Precipitation** | **mm/month** | 27 | 28 | 1 | 92 | 105 | 122 | 52 | 56 | 40 | 53 | 57 | 41 |
| **Flow** | **mm/month** | 2 | 1 | 1 | 284 | 291 | 221 | 21 | 20 | 22 | 26 | 25 | 29 |
| **DIN** | **mg/ m²/month** | 0.3 | 0.1 | 0.3 | 1949 | 2002 | 1582 | 31 | 26 | 34 | 60 | 57 | 62 |
| **DIN** | **mg/L** | 0.1 | 0.06 | 0.04 | 8 | 8 | 11 | 1.4 | 1.2 | 1.6 | 1.9 | 1.8 | 2.1 |
| **TN** | **mg/ m²/month** | 1.2 | 1.0 | 0.9 | 2143 | 2201 | 1733 | 48 | 43 | 50 | 82 | 80 | 82 |
| **TN** | **mg/L** | 0.3 | 0.1 | 0.2 | 11 | 14 | 11 | 2.2 | 2.0 | 2.4 | 2.9 | 2.8 | 3.0 |
| **DIP** | **mg/ m²/month** | 0.005 | 0.002 | 0.002 | 58 | 59 | 48 | 0.5 | 0.4 | 0.5 | 1.6 | 1.6 | 1.4 |
| **DIP** | **mg/L** | 0.001 | 0.001 | 0.001 | 0.4 | 0.4 | 0.7 | 0.02 | 0.02 | 0.02 | 0.05 | 0.05 | 0.05 |
| **TP** | **mg/ m²/month** | 0.02 | 0.02 | 0.02 | 87 | 89 | 72 | 1.0 | 1.0 | 1.0 | 2.8 | 2.8 | 2.5 |
| **TP** | **mg/L** | 0.01 | 0.01 | 0.01 | 0.6 | 0.6 | 0.9 | 0.05 | 0.04 | 0.05 | 0.1 | 0.1 | 0.09 |

**Table B.1.2.** Minimum, maximum, median and mean for all variables for the yearly average (YA), the yearly average in the snowmelt season (YAM) and the yearly average in the snow accumulation season (YAA) for eastern catchments and western catchments.

| | | Minimum | | | Maximum | | | Median | | | Mean | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Unit** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** | **YA** | **YAM** | **YAA** |
| | | **East** | | | | | | | | | | | |
| **Temperature** | **°C** | 1.3 | 7.9 | -9.9 | 9.9 | 13.5 | 0.8 | 6.2 | 10.6 | 2.7 | 6.1 | 10.6 | 3.0 |
| **Precipitation** | **mm/month** | 27 | 28 | 1 | 85 | 102 | 90 | 53 | 58 | 41 | 53 | 59 | 41 |
| **Flow** | **mm/month** | 4 | 4 | 2 | 85 | 87 | 123 | 22 | 22 | 20 | 24 | 25 | 25 |
| **DIN** | **mg/ m²/month** | 2.3 | 2.5 | 1.9 | 228 | 228 | 270 | 37 | 33 | 40 | 42 | 39 | 51 |
| **DIN** | **mg/L** | 0.2 | 0.2 | 0.2 | 7 | 8 | 9 | 1.7 | 1.5 | 2.0 | 1.8 | 1.7 | 2.1 |
| **TN** | **mg/ m²/month** | 3.5 | 3.8 | 2.9 | 321 | 360 | 341 | 57 | 55 | 58 | 67 | 65 | 71 |
| **TN** | **mg/L** | 0.3 | 0.3 | 0.3 | 11 | 12 | 10 | 2.7 | 2.5 | 2.8 | 2.8 | 2.8 | 3.0 |
| **DIP** | **mg/ m²/month** | 0.05 | 0.02 | 0.04 | 57 | 5 | 13 | 0.8 | 0.8 | 0.8 | 1.1 | 1.1 | 1.2 |
| **DIP** | **mg/L** | 0.004 | 0.001 | 0.002 | 0.2 | 0.2 | 0.7 | 0.03 | 0.03 | 0.05 | 0.05 | 0.05 | 0.05 |
| **TP** | **mg/ m²/month** | 0.1 | 0.1 | 0.2 | 67 | 11 | 14 | 1.2 | 1.2 | 1.1 | 1.9 | 1.9 | 2.0 |
| **TP** | **mg/L** | 0.01 | 0.01 | 0.01 | 0.6 | 0.6 | 0.9 | 0.05 | 0.05 | 0.09 | 0.09 | 0.09 | 0.09 |
| | | **West** | | | | | | | | | | | |
| **Temperature** | **°C** | -4.2 | 5.9 | -14.8 | 10.1 | 13.0 | 1.0 | 4.0 | 9.6 | -4.4 | 3.9 | 9.6 | -4.6 |
| **Precipitation** | **mm/month** | 27 | 26 | 1 | 92 | 105 | 122 | 48 | 55 | 38 | 49 | 56 | 39 |
| **Flow** | **mm/month** | 2 | 1 | 1 | 284 | 291 | 221 | 25 | 28 | 20 | 28 | 32 | 25 |
| **DIN** | **mg/ m²/month** | 0.3 | 0.1 | 0.3 | 1949 | 2002 | 1582 | 9 | 8.2 | 9 | 33 | 32 | 30 |
| **DIN** | **mg/L** | 0.03 | 0.01 | 0.01 | 8 | 8 | 11 | 0.4 | 0.4 | 0.5 | 1.0 | 1.0 | 1.0 |
| **TN** | **mg/ m²/month** | 1.2 | 1.0 | 0.9 | 2143 | 2201 | 1733 | 22 | 234 | 19 | 49 | 50 | 43 |
| **TN** | **mg/L** | 0.1 | 0.03 | 0.06 | 11 | 14 | 11 | 1.0 | 1.0 | 1.0 | 1.6 | 1.7 | 1.5 |
| **DIP** | **mg/ m²/month** | 0.005 | 0.002 | 0.002 | 58 | 59 | 48 | 0.2 | 0.3 | 0.2 | 1.1 | 1.1 | 0.9 |
| **DIP** | **mg/L** | 0.001 | 0.001 | 0.001 | 0.4 | 0.4 | 0.4 | 0.01 | 0.01 | 0.01 | 0.04 | 0.04 | 0.03 |
| **TP** | **mg/ m²/month** | 0.02 | 0.02 | 0.02 | 87 | 89 | 72 | 0.9 | 1.2 | 0.7 | 2.2 | 2.4 | 1.7 |
| **TP** | **mg/L** | 0.01 | 0.01 | 0.003 | 0.5 | 0.6 | 0.5 | 0.04 | 0.05 | 0.03 | 0.07 | 0.08 | 0.06 |