Effect of drivers in context of catchment characteristics on changes in DOM concentrations

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Abstract

Increasing concentration of Dissolved Organic Matter (DOM) has been observed in several lakes in North America and Northern Europe since the 1970´s and 1980´s. The main regional drivers behind these changes are decline in acid deposition, climate change and increased biomass. The underlying mechanisms associated with these drivers affect sites with different characteristics differently. This study was conducted to better understand how the site specific characteristics influence the mechanistic response to changes in the regional drivers.

With the NOMiNOR project as background, the changes in DOM concentration in six catchments in Norway (Jordalsvatnet and Glomma), Scotland (Port Charlotte and Bracadale), Sweden (Ätran) and Finland (Päijänne), were studied for the period 2000-2016. Water treatment works have obtained measures of DOM levels by monitoring proxies for DOM in their raw water sources. Data for acid deposition, climate change and biomass amount were obtained from online database services, available from organisations.

The interrelationships between the data were assessed using various statistical methods. Temporal trend analyses were performed using Seasonal Kendall tests (for variables varying with seasons), Theil-Sen estimators and linear regression. Principal component analyses were also performed on data matrices including all parameters. In addition, linear regression was used to study the correlation between colour and the climate parameters rainfall and temperature.

Significant increasing trends in DOM over the 16 year period were found in Jordalsvatnet, Bracadale, Ätran and Päijänne. All six sites had a significant ($p<0.05$) reduction in acid deposition in the period in focus. Jordalsvatnet and Ätran experienced the largest and second largest declines in acid rain, respectively. These two sites did not have any change in other governing parameters. As the acid deposition reduction correlates with DOM in Jordalsvatnet, this is probably the main driver. The mechanisms behind the DOM increase in Ätran are more unclear, due to weak correlation between acid deposition and DOM. In Bracadale and Päijänne, both reduction in acid rain and increase in biomass may be drivers for elevated DOM concentrations, with different relative importance. The high content of calcium (Ca^{2+}) and magnesium in (Mg^{2+}) in Bracadale can limit the effect of acid rain decline, so that rise in biomass is probably the main driver here. In Päijänne, these two drivers combined with the closing of local paper industry, can explain the DOM increase. Compared to Bracadale, the relative importance of biomass is possibly larger, due to higher magnitude of this effect.

Preface

I would like to thank my supervisor Rolf D. Vogt for taking me as his master student this final semester of my studies. In addition to having uniquely high competence in the field of biogeochemistry, you in person, have been very helpful, easily accessible and supportive. Furthermore, I appreciate your skill of sensing both the core and the broader view of complex material. This has provided me some important abilities independent of the topic.

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Abbreviations

BDOC	Biodegradable dissolved organic matter
CDOM	Coloured dissolved organic matter
DDL	Diffuse double layer
DNOM	Dissolved natural organic matter
DOC	Dissolved organic carbon
DOM	Dissolved organic matter
EMEP	The European Monitoring and Evaluation Programme
GHG	Greenhouse gas
HMW	High molecular weight
HPI	Hydrophilic
HPO	Hydrophobic
LMW	Low molecular weight
NDVI	Normalized Difference Vegetation Index
NIR	Near-infrared radiation
NOM	Natural organic matter
NRV	Nedre Romerrike Vannverk
OLS	Ordinary Least Squares
PCA	Principal component analysis
POM	Particulate organic matter
SK	Seasonal Kendall
SMHI	Sveriges meteorologiska och hydrologiska institut
SOM	Soil organic matter
SUVA	Specific UV absorbance
TOC	Total organic carbon
TS	Theil- Sen
WTW	Water treatment works

1 Introduction

1.1 Background

There has been an increase in dissolved organic matter (DOM) in freshwaters in northern regions the last decades, commonly referred to as browning (Finstad et al., 2016). DOM in this context is the organic matter that is formed naturally. The proposed main drivers for this increase are reduction in acid deposition, climate change and change in land-use (Kritzberg et al., 2020). Furthermore, these drivers are composite and contains many aspects, affecting DOM in freshwaters in various ways.

The DOM increase has several effects on the aquatic ecosystem. In addition it poses challenges to drinking water plants needing to remove the DOM from their raw water (Eikebrokk et al., 2018a). Browning of freshwaters is typically monitored and quantified as an increase in DOC or absorbency at given wavelengths. The spectrophotometric absorbency at e.g. 254 or 410 nm and the concentration of dissolved organic carbon (DOC) are both proxies for the DOM, as all these parameters are positively correlated. However, these correlations are not necessarily very strong. This is due to that the specific colour of DOM (i.e., absorbency at 410nm/DOC) depends on the composition of DOM. DOM with a higher composition of aromatic compounds will typically be more coloured. Likewise, the amount of DOC in the DOM varies in space and time, though on average DOC comprises around 50 w/w % of DOM.

Drinking water plants treat water from the raw water source, to obtain sufficiently good drinking water quality, due to health issues. In addition having a drinking water that is colour- and odourless is desired. One clear effect of browning is the reduction of drinking water quality. This may lead to increased use of chemicals in water treatment processes, and higher costs (Kritzberg et al., 2020). In Sweden the recommended content of DOC in drinking water is below 4 mg/L (Kritzberg et al., 2020). Drinking water regulations in Norway operate with a colour limit of 20 mg Pt/L and recommend less than 5 mg TOC/L (Lovdata, 2001). If the colour is too high in the raw water, the required level of DOM can be achieved either by abatement actions in the watershed, mitigating DOM entering the water source, or by treatment of the raw water to remove DOM. The waterworks mainly conduct and will most likely continue conducting, the last option. However extended treatment installations generate extra costs for providing drinking water services for the population (Kritzberg et al., 2020). Treatment of the raw water efficiently removes the high molecular weight (HMW) and more hydrophobic (HPO) moieties of the DOM, leaving the low molecular weight (LMW) and more hydrophilic (HPI) moieties in the treated water. Pending the water treatment method this is either due to that the HMW and HPO DOM precipitate out more readily by addition of polyvalent aluminium- or iron cations, or that the LMW DOM is small enough to pass through the filters in the membrane treatment process (Ormerod, 2017). The LMW and more HPI DOM is the most bioavailable DOM fraction. Microorganisms graze on the bioavailable DOM compounds in the distribution network, and establish a layer on the inside of the network pipes (i.e., fouling). The problem with the presence of bacteria, algae and other microorganisms on the water pipe walls are that these can release toxins that cause diseases to consumers drinking the water (Ormerod, 2017).

The absorption of radiation by the coloured dissolved organic matter (CDOM) in lakes reduces the depth of photoactive radiation (PAR) and thereby decreases the extent of photosynthesis in lakes. This can alter the biodiversity in the lake in the way that pelagic autotrophic species are favoured over benthic species (Kritzberg et al., 2020). On the other hand the allochthonous

DOM is a food source for microorganisms and provides nutrients and energy to microbes (Hartnett, 2017), thereby boosting the heterotrophic respiration. Reduced autotrophic carbon fixation and increased heterotrophic respiration shifts the surface waters from being net sinks of greenhouse gases (GHG) to becoming net sources of carbon dioxide and methane. The absorption of radiation leads also to an increase in the temperature of the epilimnion, causing a stronger lake water stratification (Song et al., 2013).

DOM is a carrier of type B (soft) metals by forming organic complexes with these. Type B metals include several of the toxic metals of environmental concern, such as mercury, lead and cadmium. In this way, DOM enhances mobilization and transport of toxic metals from soils to waters (Kritzberg et al., 2020).

1.2 Purpose of the thesis

This thesis seeks to understand better the relative impact of the drivers behind increasing concentrations of DOM in surface waters and rivers. A major issue is understanding the factors resulting in long term changes in DOM, but year-to-year and seasonal variations are also discussed. This is done by assessing water chemistry data of the raw water from 10 different waterworks with the regional trends in acid rain loading, climate and biomass of their watersheds, as well as their catchment characteristics. Norwegian Water is a national association organization that represents water industry in Norway (Norwegian Water, 2018). Norwegian Water has in the NOMiNOR project, along with several project partners, studied factors governing DOM levels at 10 sites (Eikebrokk et al., 2018a). These waterworks have monitoring data of the raw water chemistry, which are the basis if this master thesis work. These are in all in Northern Europe, in Norway (3), Sweden (3), Scotland (3) and Finland (1). The most of the catchments are located in Fennoscandia and belong to the Boreal Biogeographical Region. The Scottish sites and the two sites located on the west coast of Norway belong to the Atlantic Region (Sundseth, 2005).

The response variable of interest is the concentration of DOM. In the waterwork data for DOM, this is given by its proxies absorbency at 254 nm, DOC and/or TOC. The predictor variables studied reflect the results of former research on this topic. This research states that the main drivers of rising DOM levels are decline in acid deposition, climate change and increase in biomass (Finstad et al., 2016). Data of the past changes in acid deposition are from The European Monitoring and Evaluation Programme (EMEP, 2021a). Regarding climate change, the changes in amount of precipitation and air temperature in the catchment area are used to represent this factor. These observations were obtained from various meteorological services. The increase in biomass is assessed by the changes in Normalized Difference Vegetation Index (NDVI) values of the catchment area. NDVI is defined as:

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad \text{Eq. 1-1}$$

Here NIR and Red are the reflectance of near infrared and red wavelengths, respectively. In short terms, NDVI is a measure of greenness of vegetation (Gandhi et al., 2015). NDVI data was obtained from Copernicus (Copernicus, 2021a).

The effect the changes in these regional drivers have on increasing DOM concentrations depend on catchment characteristics. For example, the effect of the decline in acid rain on the increased

DOM is stronger in acid soils than in soils containing carbonate minerals. Likewise, the effect of increased biomass may be pending the type of vegetation. An increased precipitation amount may cause an increased flushing of DOM in till soils, though it will lead to an overall dilution in watersheds with mainly rock outcrop, shallow mineral soils or peats.

The changes in DOM caused by these regional drivers differ among the studied sites. The regions are similar in some ways and different in other ways. By linking the changes in DOM to trends in acid deposition, biomass and climate with the catchment characteristics, the aim of this study is to understand better the relative impact of the various factors.

2 Theory

2.1 Soil characteristics

Soil is the thin unconsolidated layer covering the Earth's bedrock surface. It consists of air, water, mineral particles, organic matter and living organisms. The soil consists of several horizons or layers. The composition of the horizons comprises the soil profile. It is common to state that the soil profile has two main layers, topsoil and subsoil. The topsoil is the organic-rich part. Here we find the forest floor O-horizon composed of more than 40 % organic matter which is mainly plant litter deriving from the vegetation. Below this is the A horizon consisting of humus, where the concentration of nutrients and organic matter, as well as the biological activity is high. The subsoil begins with the B horizon, often constituting the most of the soil profile. This horizon is rich on clay, and holds more moisture than the A horizon, but less organic matter. The bottom of the subsoil is called the C horizon, and consists of the weathered rock the soil originates from. Water percolating through the soil typically becomes enriched in DOM as it flow through the top soil and loses the organic load as it passes through the B horizon. When the soil becomes saturated with water, the DOM can be flushed from the topsoil and transported directly to the surface water systems. This is referred to as surface runoff or sub-lateral flow.

Carbonate minerals is one type of mineral the soil can contain. These are minerals containing carbonate and a cation, typically calcium and magnesium (Appelo & Postma, 2005). When the groundwater flows through soil with carbonate minerals, these minerals are weathered, leaching carbonate and cations to the soil (Appelo & Postma, 2005). Leaching of cations increases ionic strength, which again reduces the mobility of DOM, as will be described more thoroughly in 2.4. Moreover, carbonates will increase alkalinity. Furthermore, the form of the carbon varies between carbonate, bicarbonate and carbonic acid, and depends on the pH (Appelo & Postma, 2005).

The type of bedrock affects what type of soil that is formed in an area. If the bedrock in the boreal region consists of a high amount of carbonate minerals, Cambisols are typically formed, due to the relatively high weathering rate of these minerals. This soil contains much humus, thus it is suited for farming. Bedrock with only silicate minerals results in podzols. These are soils with less moisture and nutrients, and a higher amount of sand.

Soils in areas located below marine limit contain marine sediments. Due to this, the ionic strength in these sites is typically elevated compared to sites above marine limit.

The cation exchange capacity (CEC) is the ability of the soil to retain cations that are bound to the negatively charged surface of the soil particles. The number of negatively charged binding sites determines the CEC, and this number is high in soils with high fractions of clay and organic matter. The higher CEC, the more cation can the soil possibly hold. High CEC is typically associated with brown earth, due to the high amount of humus/organic matter.

There are several factors affecting the solubility of DOM (e.g., pH, aluminium (Al^{3+}) concentration and ionic strength) and thereby the amount that may be transported to lakes and streams. This is further described in 2.4.

Furthermore, the type of ecosystem affects how much DOM that is transported to the freshwater. Wetlands is an ecosystem that is seasonally or constantly flooded with water. Runoff from wetlands is usually rich in DOM due to the incomplete decomposition of the large pools of organic matter under anoxic conditions. During dry conditions, the discharge in streams is mainly fed by groundwater runoff, poor in DOM, and seepage from wetlands. This means that when there is little runoff, the relative contribution of DOM to waters from forests is small, while the relative contribution from wetlands is high (Laudon et al., 2011).

2.2 Lake characteristics

Most lakes are dimictic, that is, they split into two layers, one upper (the epilimnion) and one lower layer (the hypolimnion), having difference in temperature between the two layers during the winter and summer. This is due to warming from the sun during spring, summer and autumn season. Density differences causes poor circulation between the layers. During the summer, variation in discharge can cause the water chemistry in the epilimnion to vary, though the water chemistry in the hypolimnion remains stable. In the spring and fall, these temperature differences briefly disappear, and the body of water overturns and circulates from top to bottom. Raw water sources for most waterworks are lake water where the water is taken from the hypolimnion.

2.3 Dissolved organic matter

DOM is a heterogeneous mixture of partly oxidized and resynthesized water-soluble products of bacterial decomposition of lifeless biomass. In order to be defined as dissolved the organic matter molecules should be small enough to pass through a filter of size 0.45 µm (Zsolnay, 2003). Compounds exceeding this size are classified as particulate organic matter (POM). Typically, carbon constitutes around 50 % of DOM, and the rest is mostly oxygen, hydrogen, nitrogen and sulphur. DOM in freshwaters come from several processes in the watercourse and in the catchment (Hartnett, 2017). Autochthonous DOM come from inside the aquatic system itself, for example from aquatic plants and algae, while allochthonous DOM originates from the terrestrial catchment. It typically comes from the decomposition of organic soils and terrestrial plants in the watershed, and has been transported to the water with hydrological processes. It is common to distinguish between recalcitrant DOM and labile DOM. The first has HMW aromatic and HPO molecules that have low reactivity, while labile DOC is mainly LMW aliphatic and HPI compounds that are readily decomposed through microbial processes. Biodegradable dissolved organic carbon (BDOC) is an operationally defined parameter of the amount of DOM available for being microbial decomposed.

2.4 Solubility and mobility of soil organic matter (SOM)

Soil organic matter (SOM) solubility and thereby its mobility is governed by the pH, concentration of polyvalent cations and ionic strength of the soil solution. SOM has a large number of weak acid functional sites, such as carboxylic acid and phenolic groups. At the pH commonly encountered in surface waters studied in this thesis, the weak acids are generally protolyzed, rendering a net negative charge. Increasing pH causes more of the weak acids to protolyze, thereby increasing its net negative charge. With a higher density of deprotonated charged groups, DOM becomes more hydrophilic and are hence more soluble in water. The solubility of DOM itself thus increases with increasing pH (de Wit et al., 2001).

As organic matter has a net negative charge, di- and polyvalent cations in the water are attracted to the surface of DOM by electrostatic forces. This neutralizes some negative charges on the DOM surface, decreasing its solubility (de Wit et al., 2001). The solubility of DOM is thus also affected by the concentration of di- and polyvalent ions in solution. The levels of divalent cations (mainly Ca^{2+} and Mg^{2+}) are reflected by the alkalinity of the soil water. The alkalinity is the ability of the water to resist acidification (USGS, 2019). In soils with readily weatherable minerals, such as carbonates, the concentration of calcium (Ca^{2+}) is high. Likewise, high concentrations of inorganic iron and aluminium concentrations, such as found in acid soil during the acid rain period, will also cause the DOM to precipitate. The distribution of cations associated to the DOM by electrostatic attraction is described by the diffuse double layer (DDL) model (Appelo & Postma, 2005). The thicker the diffuse double layer, the higher the solubility of DOM. This is because when DDL is thick, negative potentials between the DOM compounds can better repel each other. Therefore a thinner DDL may induce flocculation, that is, lower solubility of DOM (Appelo & Postma, 2005). The thickness of the DDL increases as the ionic strength of the water decreases. This causes the solubility and thus the flux of DOM to increase with decreasing ionic strength.

There are also processes in streams and lakes that affect the quantity and quality of DOM, after it has been leached out of its soil. These processes are microbial processing through respiration, adsorption to particles causing sedimentation, and photo-bleaching caused by photo-oxidation of the CDOM (Kritzberg et al., 2020). The chemical composition, molecular structure and size affects how reactive the DOM is. Moreover, the residence time of surface waters is of importance for to which extent these processes are prevailing. In addition, DOM can have different reactivity in different environments. Other factors, as prokaryote diversity, iron and nutrient availability, redox state and temperature, also play a role for the reactivity.

2.5 Increase in DOM

In many lakes in Europe and North America, a significant increase in DOM is observed through the last decades (Björnerås et al., 2017). Considering the raw waters in the NOMiNOR project, 5 out of 10 of these fall into this category. The largest increases are found in boreal regions, especially in regions previously impacted by acid rain (Finstad et al., 2016). Production of NOM is a prerequisite for DOM ending up in freshwaters. The factors that governs the production of NOM are the amount of biochemical reactions inside living organisms and abiotic reactions occurring after the senescence and death of living cells in animals and plants (Perdue, 2009). Thus, amount of vegetation may represent the total available terrestrial NOM pool. Furthermore, different types of vegetation have different characteristics of dead plant material, which affects the microbial decomposition of these substances. The microbial activity can also be altered by various factors, for example can higher temperatures enhance this activity (Kritzberg et al., 2020). More precipitation may also have this effect, especially in dry sites. The three main drivers for higher concentrations of DOM are reduction in sulphate deposition, climate change and increase in biomass (Kritzberg et al., 2020).

2.6 Reduction in acid rain

2.6.1 Acid rain

Acid rain is rain containing air pollutants leading to acidification of freshwaters and soils (APIS, 2016). Sources of acid deposition includes emissions of sulphur dioxide, sulphate, nitrogen oxides, nitrate and ammonia (Miljødirektoratet, 2020). Not all the compounds resulting in acid deposition are necessarily acidic, such as ammonium, but they have an acidifying effect. It is common to distinguish between wet and dry deposition. Wet deposition includes the additions of acidifying pollutants through precipitation. Dry deposition is deposition of acids that occurs without precipitation. This is for example when gases and particles stick to surfaces as the ground and plants. However, not all the nitrogen entering the soil through wet and dry deposition has an acidifying effect. In watersheds that are not saturated with reactive N the nitrate is assimilated by the biota in exchange for OH^-, causing a neutralization of the acid and a net increase in biomass.

2.6.2 Effects of acid rain on soils

More H^+ in the soil means that more H^+ can exchange binding site with base cations (Mg^{2+}, Ca^{2+}, Na^+ and K^+) on the cation exchanger. Hence, base cations are mobilized and can be leached out with mobile anions, such as sulphate. Thus, acid deposition will reduce base saturation of the soil causing the soil to become more acidic. The relative effect acid rain has on ionic strength depends on the concentration of base cations naturally present in the soil. If the concentration of base cations is low, acid rain will raise the ionic strength substantially. However, the higher the concentration of base cations already is, the less is the relative increase caused by acid rain.

In soils that do not have carbonate minerals the acid rain decreases pH in freshwaters due to addition of H^+-ions. Acid rain also provides sulphate as a mobile anion allowing elevated levels of inorganic labile aluminium to be flushed out of the acid soils into surface waters.

2.6.3 Effect of acid rain reduction on DOM concentration

Decrease in acid rain increases the solubility and thus the DOM concentration by increasing the pH, and by decreasing the ionic strength and aluminium concentration in the water. Increasing pH leads to more negatively charged DOM that is more hydrophilic and thus more soluble. Decreased ionic strength leads to greater thickness of the DDL, causing greater repulsion and thus less flocculation. Thus, both pH and ionic strength are affected such that the solubility of DOM increases (de Wit et al., 2001). Decrease in concentrations of labile aluminium causes less complexation and sorption to precipitated aluminium hydroxides.

2.6.4 Acid rain changes in the Northern region

There has been a reduction in acid rain since the 1970-1980´s in the regions in focus of this study (Björnerås et al., 2017). Since the decline in deposition of acid rain largely is a finished phenomenon, this driver will likely not affect browning in the future. However, it is of interest estimating the relative effect this driver has had on the overall past increase in DOM.

2.7 Climate change

With higher air temperature, the growing season can be extended. The growing season is the period in the year when crops and other plants can grow successfully (National Geographic, 2021). This can lead to increased organic terrestrial carbon production, as well as decomposition of SOM and export of DOM to surface waters. Furthermore, increased precipitation, as well as more frequent intensive precipitation raises the water table. This gives more surface and sub-lateral runoff increasing the connectivity between organic soils and the aquatic environment (Kritzberg et al., 2020). Hence DOM in the soil will easier be flushed by the water, resulting in a larger transport of DOM to surface waters (Kritzberg et al., 2020). In addition, the more saturated the soil is with water, the more incomplete becomes the decomposition of SOM.

2.8 Biomass

2.8.1 Increase in and characteristics of biomass

Increased biomass means that the potential for SOM production is higher, and more DOM is available for being transported to waters. Several factors affect the amount of biomass in the catchment. If a region has changed from an open landscape to more forested lands, the terrestrial carbon pool increases and more DOM is available for transport to the freshwater (Kritzberg et al., 2020). The type of vegetation is also an important factor, as they have various amounts of accumulation of SOM.

Especially the type of vegetation in the riparian zone is importance in governing the DOM in surface waters. Coniferous forests have a high leaching potential of DOM. Conifer trees give litter substrate that is of lower quality for microbial processes. This leads to less complete decomposition of the litterfall, which produces more DOM.

Furthermore, a high proportion of wetlands tend to provide a higher flux of DOM. These ecosystems are major sources of DOM, in the way that they are critical interfaces between the terrestrial and aquatic environment (Hansen et al., 2018). Wetlands are in general rich on organic matter due to low complete decomposition of dead organisms. This is because these areas are seasonally or constantly flooded with water, limiting the oxygen access for microorganisms. In addition, relative low water temperatures in the boreal biome slow down the decomposition. This leads to high transport of DOM to the aquatic environment (Hansen et al., 2018).

Peatlands is a type of wetlands where the topsoil consists of peat (i.e., Histosol). If peatlands are drained in order to plant forests, its aeration will promote microbial activity and production and export of DOM (Kritzberg et al., 2020). Aeration also promotes oxidation of sulphides to sulphuric acid, which has the same effect as acid rain. The following pH reduction on the other hand reduces the solubility and mobility of DOM, as explained in 2.6.3. The sulphate also increases ionic strength, which also reduces the solubility of DOM. Thus, several mechanisms occur similarly, influencing the browning of waters in different ways.

2.8.2 NDVI

As described in 0, NDVI is a measurement of the greenness of the vegetation in an area. A change in NDVI value therefore indicates a change in amount of biomass in an area.

In order to use the NDVI values properly there is need for an understanding of the usages and limitations of this index. Since chlorophyll reflects more near infrared light (800 to 2500 nm) than red light (620–750 nm) (GIS Geography, 2020), the nominator term ($NIR - Red$) in the definition of NDVI is higher for greater chlorophyll density (Bhandari et al., 2012). Thus, the NDVI value should typically be higher in an area with forest than with grasslands. If for example a forest is established in a region where agriculture dominated before, this will result in an increase in NDVI. Summed up, NDVI can give an appropriate indication of the amount of vegetation cover in an area (Sarp, 2012). NDVI values are per definition related to the reflectance of radiation. Due to this the values can be measured by satellites.

Defined by Eqn. 1-1, the value is always in the range [-1, 1]. Negative values ($Red > NIR$) are usually the result of clouds, water and snow. The valid range of NDVI is thus between 0 and 1. Positive values below 0.1 typically corresponds to open areas of rock, sand or snow (Earth Observing System, 2021).

2.9 Statistics

Here the theoretical background in statistics for the statistical methods used in this project is presented.

2.9.1 Pearson correlation R and coefficient of determination (R^2)

The Pearson correlation R is a normalised measure of covariance, that is, a measure of how strongly two variables are linearly related. It is on the range $[-1,1]$, where a value of the extreme points means that the variables are entirely positively or negatively linearly related. Furthermore the correlation coefficient can indicate to what extent the variables in a pair are mutually dependent (information about one can be obtained by the other). The coefficient of determination R^2 is a measure of how much of the variation in a response variable that is explained by an explanatory variable.

2.9.2 Linear regression using ordinary least squares (OLS)

A linear regression model supposes that there is a linear relationship between the response variable Y and the predictor X such that

$$Y = \beta_0 + \beta_1 X \qquad \text{Eq. 2-1}$$

Using the ordinary least squares method, the coefficients β_0 and β_1 are estimated so that the residual sum of squares (RSS) is minimized (James et al., 2013). The statistical significance of this model is indicated by the Student t-test value. t is simply the calculated difference between measured and modelled value represented in units of standard error. The greater the magnitude of t, the greater the evidence that there is a significant difference.

If there is no relationship between X and Y, then it is expected that t follows a t-distribution with $n-2$ degrees of freedom. The *p-value* denotes the probability of observing a t-value $>$ $|t|$, assuming that $\beta_1 = 0$. In this study a 95 % significance level is used, so that $\mathrm{p} = 0.05$ is the limit for stating that the correlation is statistically significant. This means that if there is no true relationship between X and Y, there is only a 5 % probability that a value for t or greater will be observed.

For a linear regression model, the R and R^2 statistic are computed. The correlation (R) is a measure of how well the model fits the data. Its sign + or - indicates whether the correlation is positive or negative. The range of the coefficient of determination (R^2) is $[0,1]$. The higher the value, the larger proportion of the variability in Y is explained by the model (James et al., 2013). R^2 is the square of the Pearson correlation coefficient R (James et al., 2013). In addition, the *adjusted* R^2 of the model can be computed. This is a modified version of R^2 that takes additional noise variables in the model into account (James et al., 2013). It is always smaller than R^2, and can be negative for poorly fitted models.

2.9.3 Seasonal Kendall test (SK test)

Seasonal Kendall test (SK) is a Kendall test where seasonality is taken into account. The SK test for correlation is a non-parametric test that analyses the rank correlation between observed quantities for monotonic (consistent) trend in seasonal data. In the comparison of methods for linear trend analysis in environmental studies Hess et al. points out the SK test as one of two preferred, next to the linear regression adjusted for seasonality (Hess et al., 2001). A non-parametric test is a test that does not assume that the observations are distributed in a specific way, such as the normal distribution, or any other distribution. The main idea with rank correlation compared to the more commonly used Pearson correlation coefficient 2.9.1 is that the order of the observation sizes is in focus, and not their magnitude (Abdi, 2007).

The test statistic is used to determine the significance level of the trend. For this a two-sided Z-test is used, thus the standardized Z statistic must be calculated. The Z-test is two-sided since the test statistic S of the SK test can be positive or negative, depending on whether it indicates a positive or negative trend, respectively (Hess et al., 2001).

2.9.4 Theil-Sen estimator

The Theil-Sen estimator is relatively similar to a Seasonal Kendall test, except from the seasonal aspect. It aims in the same manner as linear regression to find the coefficients (β_0, β_1) in a linear relationship between the response Y and the predictor X. The slope β_1 is estimated by finding the slope of all pairs (y_1, x_i) of observations (as in Seasonal Kendall), and taking the median of these. The intercept β_0 is found by computing all values of $y_1 - \beta_1 x_i$, and taking the median of these. The Theil-Sen estimator is a non-parametric model which is more robust to outliers than linear regression.

2.9.5 Principal component analysis (PCA)

Principal component analysis (PCA) is a technique that summarizes the variation in the data into *principal components*. A principal component is a linear combination of all the variables in the dataset. The first principal component is the direction where the data varies the most (James et al., 2013). The following principal components are the directions where the data varies the most, simultaneously being orthogonal on the previous principal components (James et al., 2013). A PCA biplot shows both PC scores of samples (dots) and loadings of variables (vectors). This provides a view of the relative contribution from each variable along the two first components. In a dataset where variables have different units, it is recommended to standardize the data (James et al., 2013).

3 Material and Methods

The overall assessment method used in this thesis is data analysis. The waterworks have monitored a range of physicochemical parameters of their raw water over some period. These parameters include the most important parameters, such as proxies for the level of DOM. TOC, DOC, UV absorbance at 254 nm or VIS absorbance at 410 nm are all proxies for DOM as they are closely correlated to DOM, but not equivalent. Usually the difference between TOC and DOC is insignificant as the particulate organic matter concentration is generally very low. On average the carbon account for about half of the mass of DOM. Absorbance of radiation in the UV and visible (i.e., visible colour) range is determined by the amount of conjugated double bond chromophores in the DOM and the length of the conjugated bond chains. Absorbency in the UV range normalized by the DOC (i.e., specific UV absorbance (SUVA)) is thus mainly governed by the aromaticity of the DOM. Absorbency in the visible range is made possible by long chains of conjugated double bonds. Normalizing this absorbency by the DOC (i.e., sVISa) indicate the relative colour that is also reflecting the overall size of the DOM molecules. The colour is also influenced by the amount of iron (Fe), as also inorganic Fe species and the complexation of Fe to DOM give colour (Björnerås et al., 2017). However, it may as a first approximation be assumed that the distribution of carbon, aromaticity and size remain rather similar in the DOM at each site, so that higher concentration of organic carbon and UV or visible absorbency is related to higher concentrations of DOM. Other parameters monitored by the waterworks are typically pH, Fe and conductivity. The various waterworks have conducted their measurements with different frequencies varying between daily, weekly, monthly and yearly. The more observations existing, the higher is the statistical power level, that is, the probability of detecting an effect, given that the effect exists.

3.1 Characteristics of catchments

In this section, characteristics of the catchments of the studied raw waters are presented. These are properties location, size, landscape composition, vegetation, bedrock, marine limit and anthropogenic factors. As explained below in 3.1.1, some catchments were discarded due to various reasons, leaving six catchments to be studied thoroughly. Table 3.1-1 presents the name of waterwork, and name and type of water source.

Table 3.1-1. Name and type of water source, as well as name of waterwork in the six sites.

Water source (catchment)	**Type (river/lake)**	**Waterwork**
Jordalsvatnet	Lake	Jordalsvatnet
Glomma	River	Nedre Romerrike Vannverk (NRV)
Port Charlotte	River	Port Charlotte
Bracadale	River	Bracadale
Ätran	River	Kärreberg
Päijänne	Lake	Pitkäkoski

The location of each monitored water source is shown in **Error! Reference source not f ound.**.

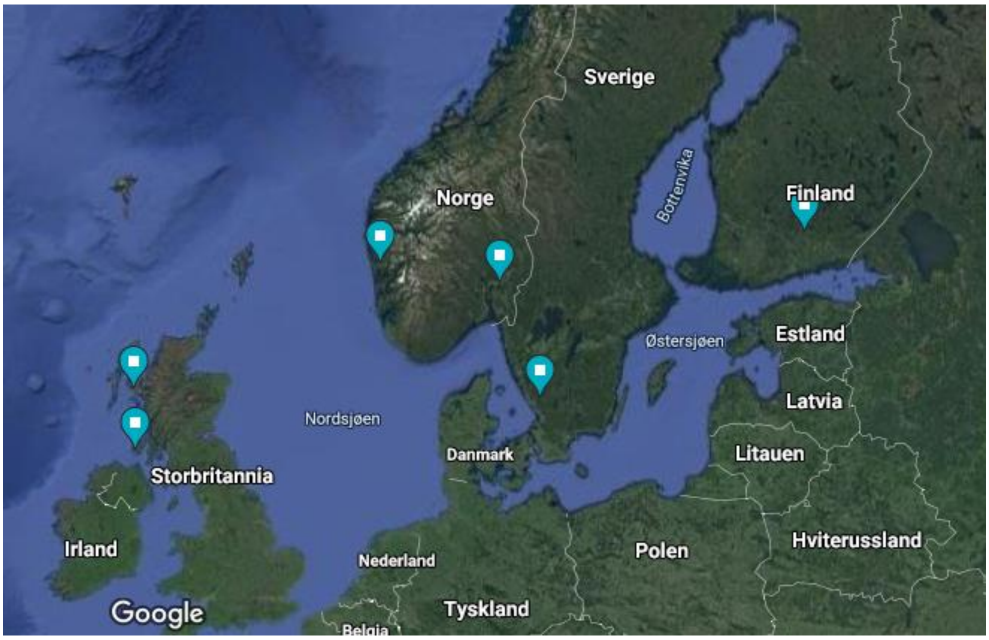

Figure 3.1-1. Map of northern Europe. Locations for monitoring DOM are denoted with blue markers. (screened from https://www.google.no/maps 30.04.2021).

3.1.1 Discarded waterworks

Four of the NOMiNOR waterworks were discarded and not included in this comprehensive analyses. These were IVAR WTW, Burncrooks WTW, Görnälverket WTW and Ringsjöverket WTW. For IVAR the issue was that water from another lake, Romsvatn, is to a varying degree pumped into Stølsvatnet (Eikebrokk et al., 2018a). The measured parameters in the raw water does thus not represent Stølsvatnet water alone, as they have introduced another factor, which we do not know the impact of. Burncrooks WTW and Görnälverket WTW lack long-term monitoring data of DOC. This is only monitored over the periods 2013-2015 and 2010-2013, respectively. Hence, this is insufficient to assess the effect of drivers on changing DOM levels. From Ringsjöverket WTW, no data was provided to this study at all.

3.1.2 Jordalsvatnet

The water source of Jordalsvatnet WTW is the lake Jordalsvatnet. It is located in western Norway, approximately 5 km north of the city of Bergen. Map of Jordalsvatnet and its watershed is shown in Figure 3.1-2. The lake has a length of about 1360 m, a width of 367 m and a depth of 50 m, that is, it is relatively small (measured in https://www.google.no/maps, 05.05.2021). The catchment is also relatively small, with an area of 9.45 km^2. The annual influx of the lake is about $16 \cdot 10^6$ m^3 (Eikebrokk et al., 2018a). The soil is thin in Jordalsvatnet. Moreover, the catchment area is dominated by fells (44.2 %), forests (22.1 %), water (7.1 %) and cultivated land (4.3 %). 20.7 % is unclassified. The fractions of urban areas (1.0 %) and bogs (0.8 %) are very small (NVE, 2021). The main bedrock is gneiss, which is associated with silicates (NGU, 2021b). Marine limit in Norway varies from zero to 220 metres above sea level (NGU, 2021c). Areas with some distance from the lake in the catchment are above marine level, meaning that substantial parts of the catchment area are above marine level (NGU, 2021a).

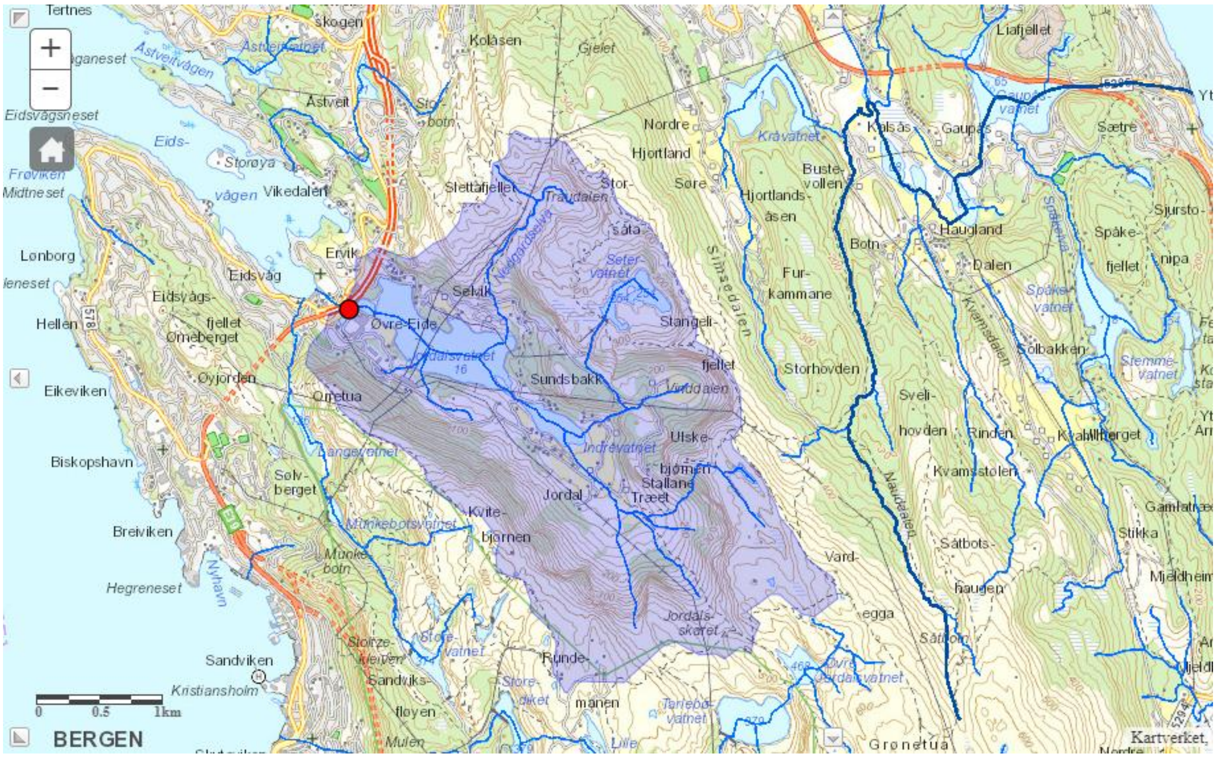

Figure 3.1-2. Map with illustration of Jordalsvatnet catchment (NVE, 2021) (Eikebrokk et al., 2018a).

3.1.3 Glomma

Glomma is located in the southeast of Norway, just upstream of the inlet at the waterworks Nedre Romerrike Vannverk. The catchment covers 38811 km^2, thus it is very large and complex. The land types dominating are forests (49.39 %), fells (27.1 %), bogs (7.52 %), cultivated land (5.31 %) and water (4.67 %) (NVE, 2021).The catchment area is shown in Figure 3.1-3. Together with the catchment of Finnish Päijänne, Glomma has the lowest precipitation amounts among the six catchments, typically around 400-600 mm/yr (Norsk klimaservicesenter, 2021). Amounts of acid rain are the smallest of the six catchment in this thesis, in contrast to Jordalsvatnet, which has the highest amounts of acid rain (EMEP, 2021b). There is large variability within the catchment, and the highest colour values are measured in the eastern part of the catchment. In the NOMiNOR project, the measured colour from this part is used in the models (Eikebrokk et al., 2018a). The bedrock consists of much sandstone, but also substantial amounts of gneiss and granite (NGU, 2021b). Hence, as in Jordalsvatnet, silicate minerals dominates. Comprehensive parts of the catchment area is above marine limit (NGU, 2021a).

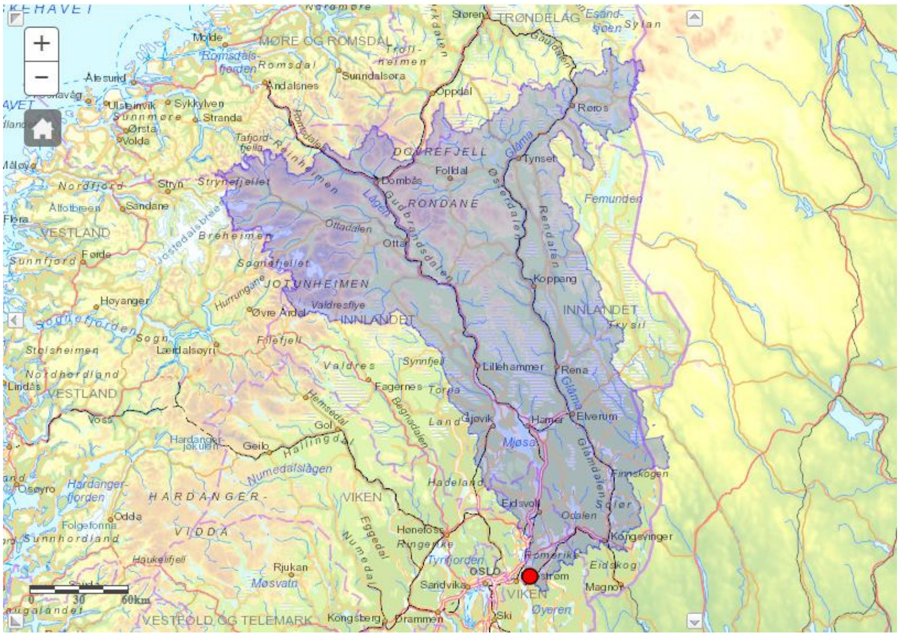

Figure 3.1-3. Map with illustration of the catchment area associated with Nedre Romerrike Vannverk (Eikebrokk et al., 2018a).

3.1.4 Port Charlotte

Port Charlotte WTW is located in the west coast of Scotland, on the island Islay in the Hebrides. Figure 3.1-4 shows the catchment area, along with the defined squared area used when handling NDVI and acid deposition for Port Charlotte. The width and length of this suggested square are approximately 1.6 km and 1.6 km. This is one of the waterworks that uses a river as its raw water source. The catchment contains a lot of grasslands, some forests, bogs and fells, in addition to the lake seen in Figure 3.1-4 (Scotland´s environment, 2021). The coastal climate is characterized by relative small fluctuations in temperature throughout the year. The minimum temperature is rarely below 0 °C, and the maximum temperature rarely above 20 °C (The Met Office, 2021). The precipitation amount in the period of study is around 1000-1500 mm/yr (The Met Office, 2021). The precipitation contains much chloride due to the close proximity to the Atlantic Ocean. Furthermore, there are also substantial amounts of carbonates in the watershed (Eikebrokk et al., 2018a). Acid rain in moderate amounts has affected the site through the latest decades. In the period studied in this thesis, the acid rain amount has declined considerably (EMEP, 2021b). The soil in the catchment is thin and contains quite much magnesium and iron (Eikebrokk et al., 2018a). The main rock types are magmatic/igneous. More specifically, felsic rocks dominate, but there is also a considerable amount of mafic rocks (British Geological Survey, 2021). Marine level in coastal Scotland is rarely above 10-15 metres (Fairbridge & Agenbroad, 2018). Hence, Port Charlotte is above marine level ("Topographic maps," 2021).

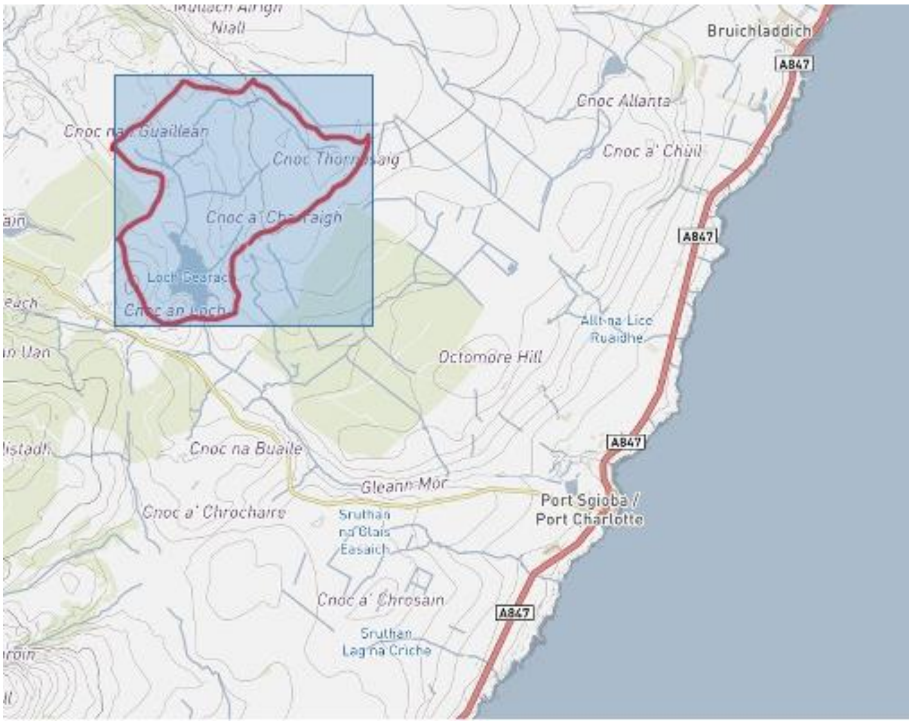

Figure 3.1-4. Map of a portion of Islay, including the catchment Port Charlotte, indicated by the red polygon. The blue square illustrates the area used when handling NDVI and acid deposition data (Scotland´s environment, 2021).

3.1.5 Bracadale

This waterworks is located on the island Isle of Skye in the northwest of Scotland. The catchment site is shown in Figure 3.1-5. In many ways there are similarities to Port Charlotte. The raw water source in Bracadale WTW is a stream, as in Port Charlotte. The precipitation amounts are relatively high, with high levels of chlorides. The temperature does not vary considerably throughout the year, typically ranging between 0 °C and 20 °C (Eikebrokk et al., 2018a; The Met Office, 2021). The acid rain has also here been reduced in the period in focus, but the average yearly amounts are approximately 19 % lower than in Port Charlotte (EMEP, 2021b). Moreover, thin soil with high magnesium and iron content is present also here. The rock types are magmatic/igneous, and are composed of felsic and mafic rocks. In addition the eastern part of Isle of Skye consists of mainly sandstone and mudstone (British Geological Survey, 2021). The area is covered mostly of grasslands (Scotland´s environment, 2021). As Port Charlotte, Bracadale is above marine level ("Topographic maps," 2021).

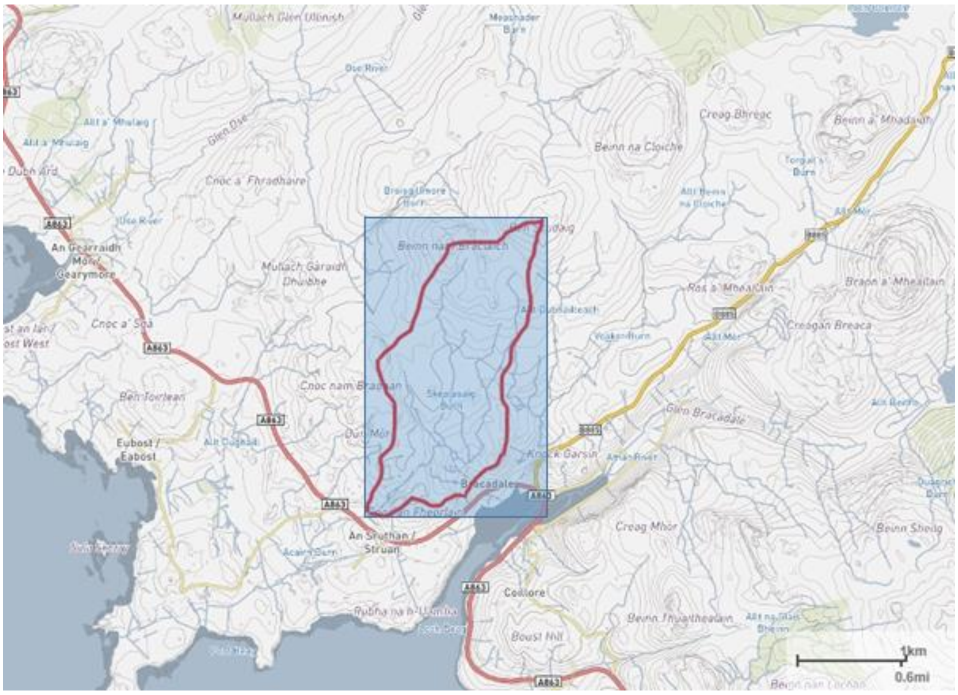

Figure 3.1-5. Map of a portion of Isle of Skye, including the catchment Bracadale, illustrated as the red polygon. The blue square illustrates the area used when handling NDVI and acid deposition data (Scotland´s environment, 2021).

3.1.6 Ätran

Ätran is a river located in the southwest of Sweden that is used as the raw water source for the waterworks Kärreberg. The area of the watershed is 3339 km^2 (SMHI, 2021), and is shown in Figure 3.1-6. This catchment had the second highest deposition of sulphate among the six catchments. Like all the others, the acid deposition has decreased. The precipitation amount in the Ätran area is around 900-1500 mm/yr (SMHI, 2021).

Its water chemistry is quite similar to the two Scottish catchment, with high levels of chloride, sulphate and carbonates. The river Ätran and its tributaries have been extensively limed since 1978, which probably has contributed largely to the carbonate concentration (Eikebrokk et al., 2018a). The bedrock mostlt consists of types of gneiss, but also some granite (SGU, 2021).

The land-use of this catchment is dominated by forest, posing 70 % of the catchment area. Cultivated land also poses a relatively large part of Ätran, with 14 %. Moreover the catchment contains some water areas (5.5 %), other land areas with vegetation (5.10 %), mires and wetlands (3.8 %) and the urban components of urban centres (1.2 %) and impervious surfaces (0.43 %) (SMHI, 2021).

Considering the soil type, it is dominated by till, which comprises 42 %. Other soil types present are peat (15 %), sandy soils (10 %), and thin soil including bedrock outcrop (16 %). Surface waters and streams cover 5.5 % (SMHI, 2021).

Map services providing marine limits were not found for Sweden. However, based on topographic map ("Topographic maps," 2021), the most of the catchment area is above marine limit, due to that marine limit in southernmost parts of Sweden is 20 metres above sea level (SGU, 2020).

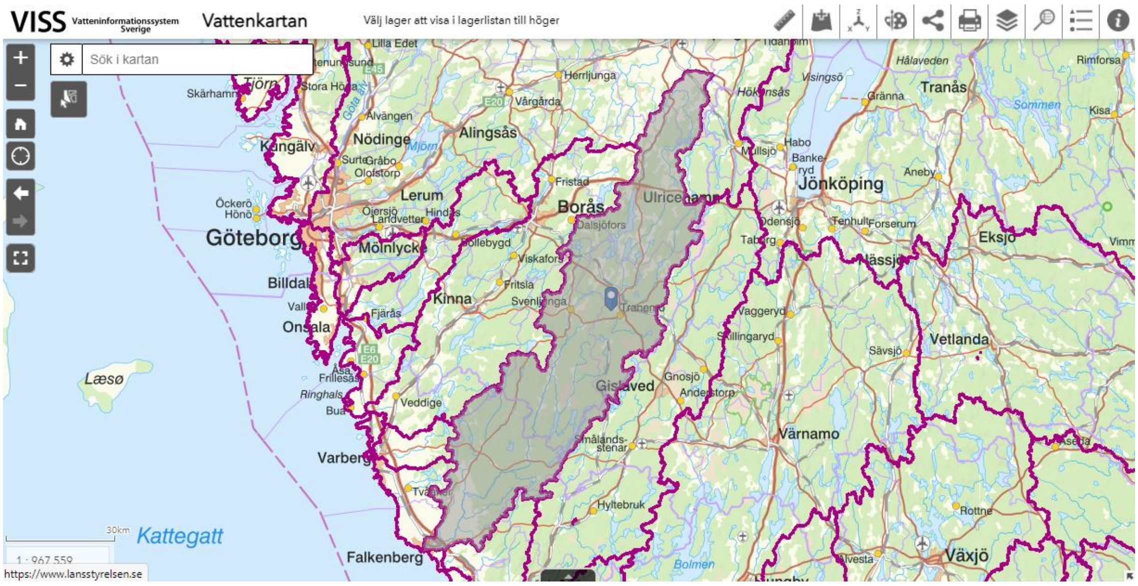

Figure 3.1-6. Map of a southern Sweden, including the catchment Ätran (VISS, 2021).

3.1.7 Päijänne

The raw water source of Pitkäkoski waterwork in Helsinki located south in Finland is the catchment of the lake Päijänne, which is a very large catchment. The suggested square used while handling NDVI and acid deposition data in this study covers 30596 km^2 (National Land Survey of Finland, 2021). A map of a portion of southern Finland is shown in Figure 3.1-7, including the catchment site of Paijanne. Lake Päijänne is the third largest lake in Finland. The lake covers 1116 km^2 with a mean depth of 16 m. The theoretical residence time is 2.2 years (Eikebrokk et al., 2018b). The catchment area is by far dominated by forests, with some grasslands and surface lakes with their tributary rivers (National Land Survey of Finland, 2021). Since its location is relatively far from the ocean, this lake is not heavily affected by sea salt from the ocean. The site receives relatively low levels of rainfall, 500-700 mm/yr (National Land Survey of Finland, 2021). The acid deposition is relatively low, second smallest in this study (EMEP, 2021b). Furthermore, the lake water has experienced a clear decrease in chloride concentration, which is probably related to the closing of local paper industry (Eikebrokk et al., 2018b). As Finland´s land except from the extreme south is dominated by coniferous forests, the trees in the catchment area are conifer trees (Sandvik, 2021). Information about marine limits in Päijänne were not found.

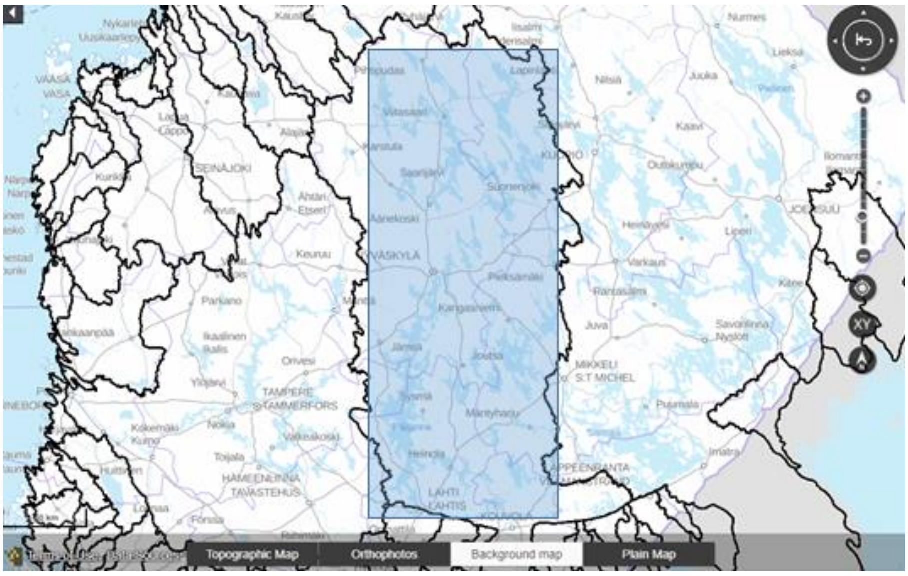

Figure 3.1-7. Map including the Päijänne catchment, which is the largest area in the middle (National Land Survey of Finland, 2021).

3.2 Representation of catchments in RStudio

The catchments have been previously studied in the NOMiNOR project. Since this thesis is about the catchments it was necessary to find a way to represent the relevant catchments in RStudio, where the statistical assessments were performed.

Since a catchment is a defined area the first step was to find the location of the catchments. This was done by using various internet based map services in Norway, Sweden, Finland and Scotland, and by studying maps and satellite photos of the areas. In Norway and Sweden it was possible to download shapefiles (.shp) for the catchments Jordalsvatnet, Glomma in Norway (NVE, 2021) and Ätran in Sweden (VISS, 2021). These files can be read in RStudio and the NDVI values can be extracted for the area the shapefile represents. For the catchments where it was not possible to aquire shapefiles, a rectangle was instead defined representing the same area of approximately the same size as the catchment. The corners of this rectangle was then represented with a range of latitude (south-north) and longitude (west-east) coordinates. The uncertainty when doing this is that the NDVI characteristics as well as the sulphate and nitrate deposition may be different from these characteristics from in the exact polygon. However, since the rectangle was limited to not reach far out from the polygon and simultaneously include a substantial part of it, this approximation was assumed to be representative of the catchments. The exact coordinates used for defining the Scottish and Finnish catchments are given in Appendix A Locations of catchments.

In the following, the characteristics of the data for the DOM proxies, as well as the three main key drivers for the increase in DOM are described for the various catchments. In addition, it is described how the data associated with these drivers was obtained. Summed up, a range of online databases that provide observations and modelled values for climate parameters, NDVI and acid rain parameters were used. As these databases have data for a longer time period than the monitoring period for DOM proxies, a selection of time range was made. Acid deposition data was obtained from the European Monitoring and Evaluation Programme (EMEP) (EMEP, 2021a). Since the start year of their gridded deposition values is 2000, the data associated with the other variables were also selected to start at year 2000, except from NDVI data, that started in 1999.

3.3 DOM

In Table 3.3-1 the temporal range, resolution and type of proxy for the six catchments are presented.

Table 3.3-1. Overview of type of proxy for DOM at the studied catchments, and its number of observations and resolution.

Catchment	**Start date (DMY)**	**Stop date (DMY)**	**Total number of observations**	**Resolution (frequency)**	**Comments**
Jordalsvatnet **Colour**	12.01.1999	09.03.2015	From 1999: 532 From 2000: 526	Variable, every week for several years	
Glomma Colour	04.01.1999	16.12.2014	From 1999: 571 From 2000: 521	Variable. Mostly every week/every second week	
Glomma TOC	24.02.1999	15.12.2014	From 1999: 291 From 2000: 272	Variable. 2010-2014: Mostly every week/every second week	
Port Charlotte **Colour**	24.01.2000	13.10.2015	286	Variable. Mostly 17-27 observations every year, relatively evenly distributed	2001 and 2002 have 78 and 15 observations, respectively. The latest has most of its observations in the second half of the year These are the extreme years. TOC and DOC also exists in the dataset, but the frequency is low.
Bracadale **Colour**	10.01.2001	09.05.2016	293	Variable. Mostly approximatel y 12 times yearly, relatively evenly distributed	2001 and 2002 have 63 and observations, respectively. These are the extreme years.

Ätran Colour and TOC	07.02.2000	16.12.2013	Colour: 78 TOC: 78	Once every second month, in month number 2, 4, 6, 8, 10 and 12 every year. No observations for 2012.	
Päijänne Colour and TOC	03.07.2001	21.04.2015	Colour: 60 TOC: 59	Variable. Once every second month for 2004-2010, months 2, 4, 6, 8, 10 and 12 except from 2008.	For remaining years, there are 1-5 observations.

3.4 Climate change

Data for air temperature and rainfall were in some cases monitored along with the raw water data by the waterworks. However, to get a broader and more holistic view on this, observations were obtained from online databases. Weather stations in the vicinity or within the watershed that had data for the period that as the assessed WTW data were selected. It was assumed that the changes in climate at this weather station represented the evolution in the catchment. The resolution of the climate data for the six catchments varied from daily to monthly.

In addition, the growing season for each year was found for Jordalsvatnet and Glomma. The method for determining the growing season was finding a continuous interval of the year where the mean daily temperature was 5 C° or higher. The time period and resolution characteristics of the climate parameters used in this study is shown more detailed in Appendix B Characteristics of driver´s data.

In the following concrete description, it is described how climate data has been obtained for the catchments.

3.4.1 Jordalsvatnet

Climate data from Norsk klimaservicesenter was used (Norsk klimaservicesenter, 2021). The meteorological station Bergen-Florida was used to represent Jordalsvatnet. Rainfall data with monthly resolution and temperature data with daily resolution was downloaded. Daily temperature measurements makes it possible to find the length of the growing season. Each temperature value is the mean temperature for that specific date. It was assumed that monthly total rainfall was sufficiently detailed.

3.4.2 Glomma

Also for the Glomma catchment Norsk Klimaservicesenter (Norsk klimaservicesenter, 2021) was used to find the rainfall amount and air temperature. For Glomma, the meteorological station Sjoa was used for rainfall data and the station Lillehammer-Sætherengen was used for air temperature data. This was due to that these sites contained data for the period in focus for Glomma, 2000-2014. Both stations are centrally located in the catchment area.

3.4.3 Port Charlotte

Climate data for Port Charlotte were obtained from the national meteorological service for UK, The Met Office (The Met Office, 2021). The three meteorological stations, Tiree, Dunstaffnage and Ballypatrick Forest, are situated on the island Islay, where the catchment is located. At each station, there are monthly observations for the climate parameters rainfall, maximum temperature and minimum temperature. The observations of the station at Tiree were used to represent the historic development of the catchment associated to Port Charlotte.

3.4.4 Bracadale

The method for obtaining climate data for Bracadale was similar to Port Charlotte. The three nearest available stations to Bracadale are Tiree, Dunstaffnage and Stornoway Airport. Tiree station was used for representing Bracadale.

3.4.5 Ätran

Climate data for this Swedish catchment was obtained from the Swedish Meterological and Hydrological Institute (SMHI) (Swedish Meterological and Hydrological Institute, 2021). The dataset for the meteorological station Ullared A, in the middle of the catchment, was used to represent the catchment.

3.4.6 Päijänne

Weather data from the Finnish Meteorological Institute were used for Päijänne (Finnish Meteorological Institute, 2021). The meteorological stations Joutsa Savenaho and Sysmä Joutsjärvi were used to represent the temperature and precipitation, respectively, in this catchment area. Joutsa Savenaho is located about 25 km east of the lake, while Sysmä Joutsjärvi is about 15 km east of the lake. These stations were selected because they provided almost complete set of monitoring data throughout the period of interest for Päijänne.

3.5 Biomass

3.5.1 General considerations of using NDVI for representing biomass

In this study, changes in NDVI values are used to represent changes in biomass in the catchments during the latest decades. This is a remote sensing measurement of the greenness of the vegetation in a grid.

An assessment of the drivers behind these changes was not performed. Thus, the factors governing the changes in NDVI are not known. An increase in biomass can be a result of higher temperatures, accumulation of reactive N and change in land-use, as reorganization of an area from pasture to forests.

3.5.2 Characteristics of Copernicus Global Land Service

For NDVI data, the Copernicus Global Land Service was used. This is the European flagship programme of Earth Observation (Copernicus, 2021a). In the databases of Copernicus NetCDF files (.nc) contain the NDVI data. The main reasons for selecting the Copernicus service is a reasonable resolution of the gridded data (1 km x 1 km), and advantages associated with performing the analyses. A package (ncdf4) that can read the .nc file can be installed in RStudio. As the data analyses were done in RStudio as well, it was beneficial that the NDVI data was available on the same data program. There are 36 files with NDVI data per year, associated with the 1st 11th and 21st in each month, ranging from May 1998 to June 2020 (Copernicus, 2021b). Each NDVI product covers accumulated observations for a period of 10 days, up to the 10th, 20th and the last day of the month. This period is extendable up to 16 days. As exemplified in the product manual, the file c_gls_NDVI_201308210000_GLOBE_VGT_V3.0.1.nc corresponds to the accumulation period from 16.08.2013 to 31.08.2013. If there are three or more observations from the last 10 days, then only observations from these 10 days are used (Tavares et al., 2020). Otherwise, observations from the last 16 days were used. In this study, the NDVI values from the summer months June, July and August were used. Hence nine observations per year were included in the analyses. This practice follows Finstad et al. in their article regarding drivers for surface water browning (Finstad et al., 2016). The reason for this is that the greenness of vegetation is expected to be highest during summer, indicated in Figure 3.5-1, which shows NDVI values for one year, with a resolution of three values per month. The behaviour of NDVI is illustrated with Päijänne in 2016. This can also be seen in Figure 3.5-2, which shows NDVI values corresponding to the data collected 1st day of each month, for the years 1999-2015. The fluctuation and change in NDVI reflect the seasonal variation and long term evolution in biomass production in the catchments. The long-term change is most important, even though it could have been interesting to study the changes in the seasonal variations too. To cover all the years of which DOM has been measured by the water treatment works, NDVI data was downloaded for the period 1999-2016. Including 1999 was desired although the other variables were analysed from 2000, because the biomass effect was assumed to come with some time lag (Finstad et al., 2016).

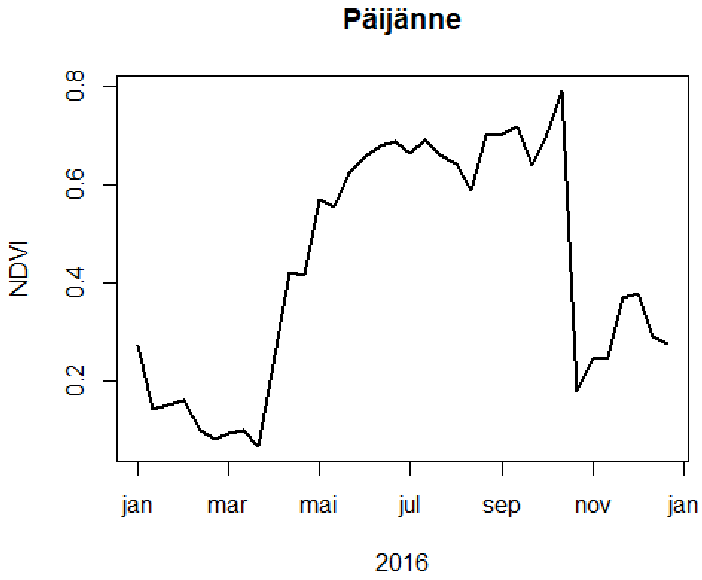

Figure 3.5-1. NDVI for Päijänne in 2016.

One .nc file contains NDVI values for the whole world on the selected date. Among the files handled in this thesis, these were the largest, with a typical file size of 380-480 MB. The world is divided into pixels. The resolutions 1 km x 1 km (1km) was available for the period in focus, 1999-2016. Since the catchments typically stretch over several square kilometres, each site is the average of many NDVI values.

In the NetCDF file each NDVI value is associated with a coordinate. The coordinate system of the Copernicus products is the World Geodetic System 84 (WGS 84), and the coordinates are given as decimal degrees (Smets et al., 2020). In order to retrieve the NDVI values of a catchment, NDVI values corresponding to the coordinates of the catchment needed to be extracted from each NetCDF file.

3.5.3 Challenges with Copernicus Global Land Service

Snow cover and persistent clouds during the 10 day monitoring periods lead to lack of observations (Smets et al., 2020). This is illustrated in Figure 3.5-2. The line in the plot is discontinuous, and the holes typically appear in the winter when there is a snow cover.

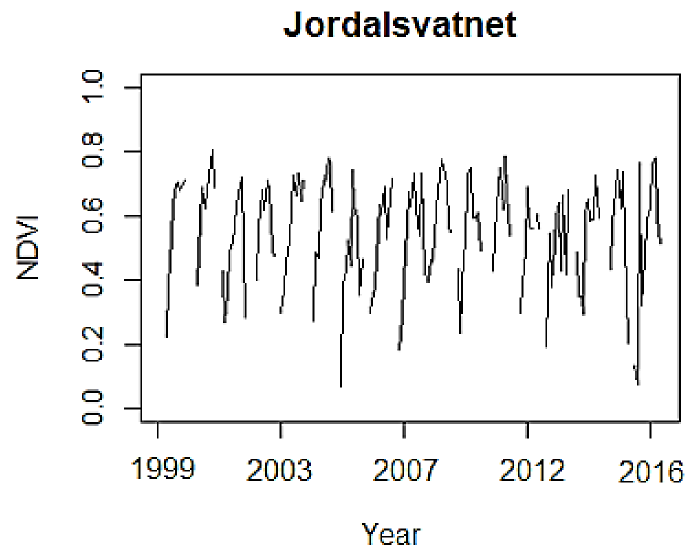

Figure 3.5-2. Line plot of NDVI values for Jordalsvatnet from January 1999.

Lacking NDVI values takes the value NA, meaning Not Available. In addition to NA values, there were also NDVI values that are not valid, in the way that they are outside of the defined valid range of [-0.08, 0.92] as is described below. Also these data were discarded. Non-vegetation objects, such as water, give NDVI values outside the defined range of "valid" NDVI values (Smets et al., 2020). Thus, it was necessary to identify these observations falling outside this interval of [-0.08, 0.92] in RStudio, and discard these, so that these were not included in the analyses.

Based on the documentation of the NDVI 1 km Product Version 3 (the product used in this thesis), Copernicus operates with a physical value (PV) and a digital number (DN) for each observation (Smets et al., 2020). The PV is used in this thesis. This value is derived by using the DN through the following relation:

$$\text{Physical value (PV)} = \text{Scaling} \cdot \text{DN} + \text{Offset} \qquad \text{Eq. 3-1}$$

Here $\text{Scaling} = \frac{1}{250}$ and $\text{Offset} = 0.08$ (Smets et al., 2020). This is because the valid DN is on the range [0, 250], which means that the defined range of valid PV is [-0.08, 0.92]. This can be seen as a small transformation of the common $[0,1]$ range of NDVI (since negative values are undesired).

To check if the NDVI data from Copernicus represented the biomass status at each site in an appropriate way, the ratio of NDVI values being NA was calculated. In addition, the ratio of values being either NA *or* outside defined valid range was calculated. In this check one value is the ratio of NDVI values being NA in one catchment at the date given in a specific .nc file. Thus, for Port Charlotte using NDVI values for the period 1999-2015 (17 years), there are totally 17 · 9 = 153 values. The computed NDVI value for Port Charlotte is the mean of 16 NDVI values, each corresponding to a unique location in the catchment. If for example three of these 16 are NA values, the NA ratio for Port Charlotte this specific file is 3/16. Summed up, there were acceptably low fractions of NA values for all catchments. The catchment ending up worst was Glomma, where 50 % of the dates had a ratio of lower than approximately 0.1, and the rest 50 % approximately between 0.1 and 0.3, except from six outliers. The details can be seen in Appendix C NDVI data.

3.6 Acid deposition

Data on acid deposition was downloaded from the databases of the European Monitoring and Evaluation Programme (EMEP, 2021a). This is an international co-operative programme for monitoring the effect of abatement actions implemented for solving transboundary air pollution problems in Europe. EMEP has five centres. The Meteorological Synthesizing Centre provides gridded depositions of sulphate (SO_4^{2-}) and nitrate (NO_3^-) for Europe. These data are used in this thesis (EMEP, 2021b). These files are also of the type NetCDF, so that they could be read into RStudio. The file sizes are ~77 MB, about a 5-6-fold smaller than the .nc files containing NDVI values. The grids are 0.1° x 0.1° longitude-latitude. This corresponds to about 10 km x 10 km. In RStudio the values for deposition of sulphate and nitrate, both for wet and dry deposition were extracted. The reason for extracting deposition values of these compounds is that the primary emitted acid rain precursor pollutants SO_2 and NO_x are converted through pathways in air, ending up as SO_4^{2-} and NO_3^- (Irwin & Williams, 1988).

The amount of acid deposition is highly dependent on anthropogenic activities in the downwind region. Emissions of SO_2 and NOx, leading to acid rain, have significantly declined in Europe since the late 70’s. This has led to a substantial decrease in in the acid rain deposition that has been tailing off during the period 2000-2016, which is studied in this thesis. Since the total deposition amounts of sulphur and nitrate per year are the most important observations associated with acid deposition, files containing their yearly total deposition were downloaded and handled. Appendix B Characteristics of driver´s data provides the time frame and format of acid rain observations that were studied for the six catchments.

3.7 Statistical assessment

A set of statistical methods were employed to perform trend analysis of the explanatory parameters for the possible trends in DOM. The explanatory factors that were assessed were rainfall, temperature, NDVI, sulphate and nitrate deposition. Possible temporal trends in these variables were individually examined, using the three types of temporal trend analyses: i.e., linear regression, Theil-Sen estimator and Seasonal Kendall test. Furthermore, linear regression was performed to investigate the effect of climate parameters on DOM. Principal component analysis was also performed, to examine all parameters simultaneously, excluding parameters found to be dependent in Pearson correlations. The RStudio script for performing these analyses are provided in Appendix G RStudio scripts.

3.7.1 Pearson correlation

Pearson correlations *R* between variables were computed to indicate to what extent information about one variable can be obtained by the other. The variables included in these computations are described in Table 3.7-1. It seems reasonable to assume that these variables are not independent.

Table 3.7-1. Overview of the variables for which correlations were computed.

Variables	Comments
Colour, TOC	Glomma, Ätran and Päijänne
Sulphate, nitrate	All catchments
Maximum temperature, minimum temperature	Port Charlotte and Bracadale

The values for computing these correlations, along with the results, are presented in Appendix D Pearson correlations.

3.7.2 Time trends in NDVI and acid deposition

In addition to linear regression, the Theil-Sen estimator was used for identifying significant effects of explanatory variables lacking the seasonal aspect. All NDVI data used in this study is associated with the same season, that is, the summer. Data for acid deposition described total annual deposition values, thus, these data also lack the seasonal aspect. Considering NDVI, it is reasonable to assume that a potential effect on DOM from an increase in biomass will appear with some time lag. To avoid constructing a trend which does not exist (data-dredging), a fixed time lag of one year was selected in this thesis, following Finstad et al (Finstad et al., 2016). Assessments in Finstad et al. evaluating changes in environmental parameters, were primarily based on this method (Finstad et al., 2016). As this is a non-parametric method it is less sensitive to outliers than OLS. Thus, it was used for determining the significance of the change in annual trends in NDVI, as well as sulphate and nitrate deposition. In addition, this estimator was used to fit a model for length of growing season or the catchments Jordalsvatnet and Glomma, where the temperature data provided daily mean temperatures.

3.7.3 Time trends in DOM and climatic data

A seasonal Kendall (SK) test was performed to identify temporal seasonal trends in the variables DOM, rainfall and temperature of which there exist seasonal data. Here the three months in winter (December, January, February), spring (March, April, May), summer (June, July, August) and fall (September, October, November) were considered as season $p = 1$, 2, 3 and 4, respectively. To associate the observations for each winter as the same season, the year variable for observations for December were transformed by subtracting 1. For example was December 2003 grouped as the same season as January and February 2004.

As described in the theory chapter (2.9.3), the model computed the difference between the observed value of a variable X in year i and j, where i < j, within each season. Hence, for each specific season in a specific year, the SK model associates only one X value. In the data several observations occur within the same season in the same year. This issue was handled by averaging the observed values. The null hypothesis for a variable X is that there are no temporal trends in any season. The alternative hypothesis is that there exist a monotone trend of X in one or more seasons.

Based on the resulting p-value it was determined whether there had been a significant change in each parameter, within each catchment. In addition, the resulting model slope was an indication of the magnitude of the potential change.

3.7.4 Linear regression for explaining DOM with climate data

Linear regression models for colour as a function of rainfall, as well as models for colour as a function of temperature were fitted, using the ordinary least squares method. This was done to assess the response to short term variation (episodes) and seasonal fluctuation. Each colour measurement was coupled to a climate data. The manner in which this was conducted depended on the resolution of the climate data, thus, this was done differently for different sites. If any temperature or rainfall observations was lacking, the colour observation this was supposed to be associated to was simply not included in the model fitting. The method for pre-processing the data is shown in Appendix E Data used in R scripts.

3.7.5 Principal component analysis (PCA)

PCA was performed for all catchments, by using colour, rainfall, temperature, NDVI and sulphate deposition as variables. The NDVI and sulphate data are used with an annual resolution in this assessment. Hence, all the other variables in the PCA was used with this resolution. Annual values for colour, rainfall and temperature were acquired by averaging these variables for each year. Although TOC observations are available for catchments Glomma, Ätran and Päijänne, the TOC parameter was not included in the PCA´s, due to relatively strong correlations with colour. Moreover, nitrate was not included due to the strong correlation with sulphate. For the Scottish sites, the temperature variable Temp is derived from the maximum temperature. Due to strong correlation between the maximum and minimum temperature, the last was not included in the PCA´s.

A clear challenge with performing PCA on the water data of these catchments appears when the observations of colour are not equally distributed throughout the year. For example, for Päijänne, there is only one observation in 2001, 2002 and 2015, from July, February and January, respectively. This makes the yearly mean sensitive to the date of one or few individual observations. As seen on the characteristics of proxies for DOM in 3.3, this issue is most in prominent in Päijänne. Considering climate data, the observation station Joutsa Savenaho, providing monthly temperature data for Päijänne, missed 14 monthly observations for the period 2000-2015. Since temperature is highly variable with months, the missing observations were filled in to avoid the temperature variable in the PCA from being sensitive to missing observations. The missing observations were replaced by the mean of the remaining observations from the actual month. For example, the value for July 2001 was estimated by taking the mean of the other temperatures in July. The assumption of no long-term change in month temperatures seems reasonable due to that no long-term seasonal change was found by the Seasonal Kendall test.

In the Ätran monitoring data there was no colour measurement from 2012. To obtain a reasonable colour value for 2012, the model derived from the Seasonal Kendall test (Chapt. 4.1) was used to predict a mean value for colour for 2012.

Furthermore, it is important to note that these analyses were performed to get an overview of the variation in the data, and were not used alone for drawing conclusions.

4 Results

4.1 Time trends in DOM

The characteristics of the SK tests for DOM proxies are presented in Table 4.1-1. A significant temporal increase in DOM was found in Jordalsvatnet, Bracadale, and Päijänne, while the increase at Ätran was barely not significant for the colour proxy, but significant for the TOC proxy. The significance levels are clearly highest in Jordalsvatnet and Päijänne, that is, the strongest indications of an increase are found there. The absolute rises in Bracadale, Ätran and Päijänne are about twice the rise in Jordalsvatnet. The plots of colour and TOC against time are given in Figure 4.1-1 and Figure 4.1-2, respectively.

Table 4.1-1. Computed p-values for SK tests for proxies of DOM. The SK test slopes are also included for the models where the change is statistically significant to a 95 % ($p < 0.05$) level.
**: Slightly not statistically significant.*

Catchment	Two-sided p-value colour	Change y^{-1} colour	Two-sided p-value TOC	Change y^{-1} TOC
Jordalsvatnet	0.000	0.464		
Glomma	0.234	-	0.159	-
Port Charlotte	0.286	-	-	-
Bracadale	0.041	0.963	-	-
Ätran	0.059*	0.912	0.003	0.255
Päijänne	0.000	1	0.000	0.168

4.1.1 Plots of all catchments

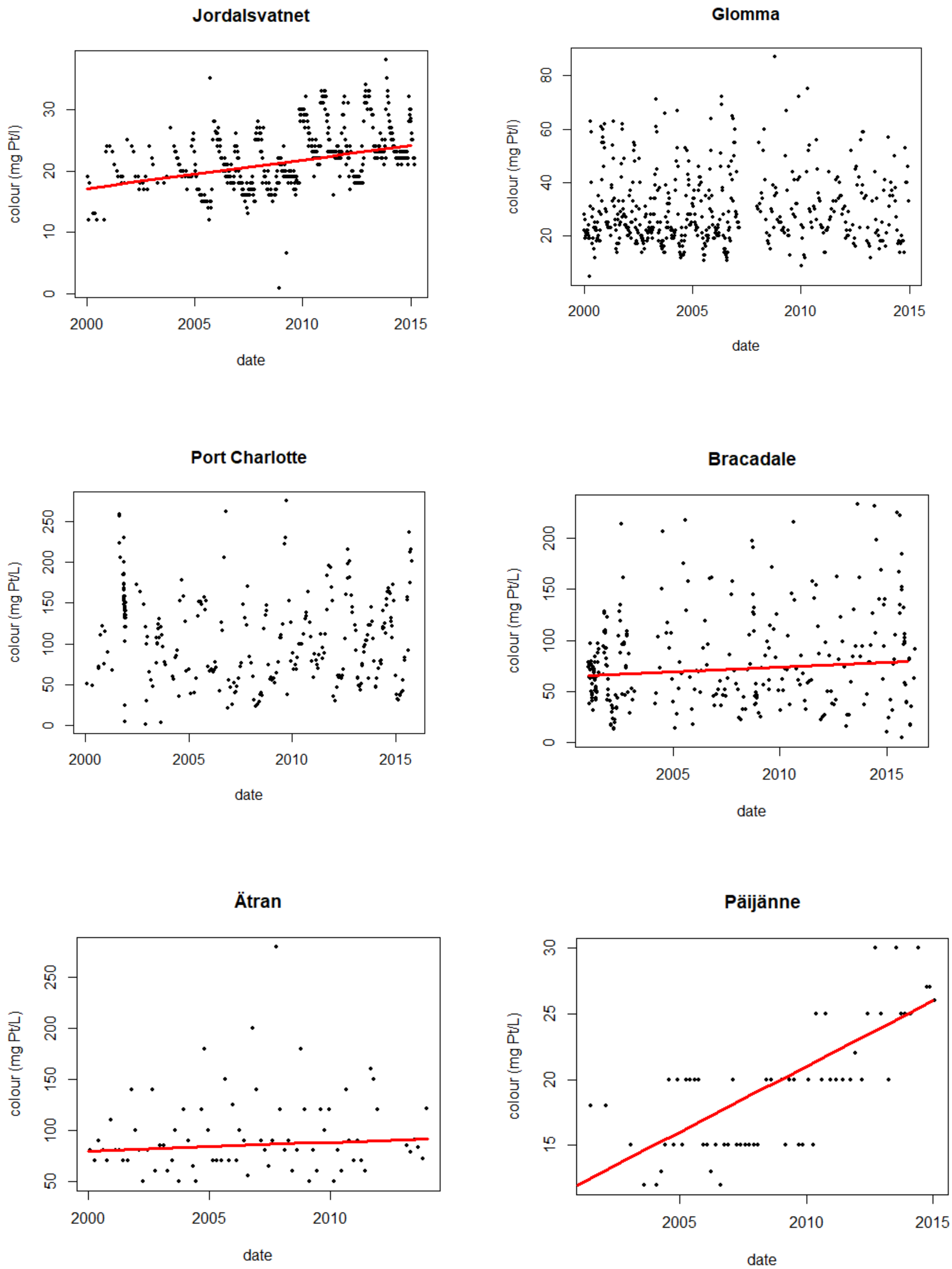

Figure 4.1-1. Plots of colour against date for the six catchments. The fitted curve of the Seasonal Kendall model are included for the sites where this test showed statistical significance.

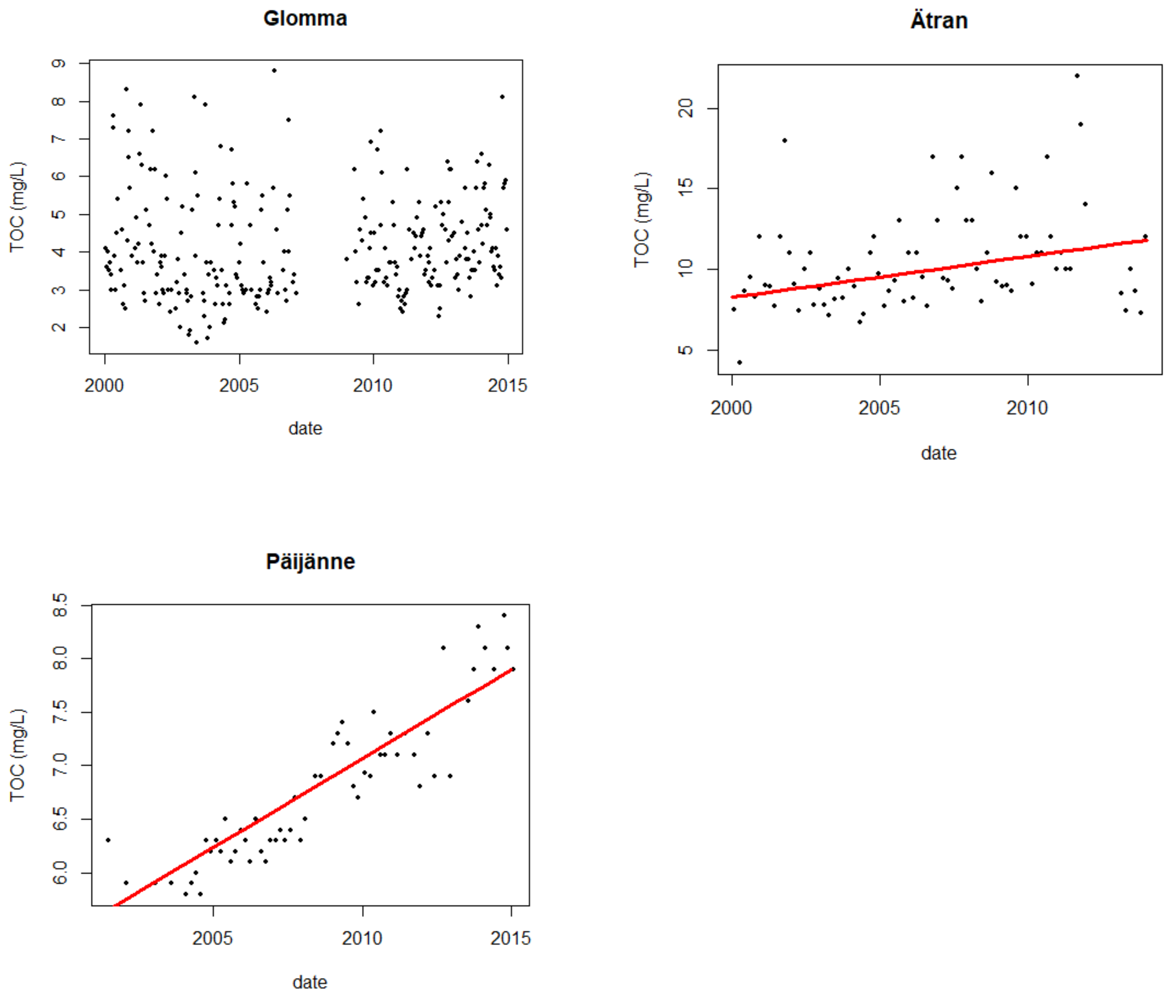

Figure 4.1-2. Plots of TOC against date for the catchments Glomma, Ätran and Päijänne. The fitted curve of the Seasonal Kendall model are included for the sites where this test showed statistical significance.

4.2 Time trends in climate

Table 4.2-1 shows the characteristics of the SK tests for climate variables the six catchments. Strictly speaking, there was no statistically significant change in rainfall amount at any sites. However, precipitation in Port Charlotte and Bracadale, both represented with the observations from the meteorological station Tiree for periods 2000-2015 and 2001-2016, respectively, may have experienced a slight, although insignificant, increase. Likewise, there are no significant temperature changes in any seasons in any catchments. The plots of rainfall against date and temperature against date are shown in Figure 4.2-1 and Figure 4.2-2, respectively. In addition, the length of the growing season seems unchanged for the Norwegian sites, seen in Table 4.2-2 and plotted in Figure 4.2-3.

Table 4.2-1. Computed p-values for SK tests for the climate variables rainfall and temperature. The SK test slopes are also included for the models where the change is statistically significant to a 95 % ($p < 0.05$) level. A slope field containing "-" means that the change is not statistically significant.
**: Slightly not significant to an absolute 95 % level.*

Catchment	Two-sided p-value rainfall	Change rainfall mm y^{-1}	Two-sided p-value temperature	Change temperature mm y^{-1}
Jordalsvatnet	0.468	-	0.742	-
Glomma	0.385	-	0.359	-
Port Charlotte	0.068*	+1.26	Max: 0.597 Min: 0.538	-
Bracadale	0.056*	+1.24	Max: 0.930 Min: 0.391	-
Ätran	0.576	-	0.894	-
Päijänne	0.345	-	1	-

Table 4.2-2. Characteristics of Theil-Sen model of days in growing season as a function of year.

Catchment	p-value	Change growing season (days y^{-1})
Jordalsvatnet	0.065	-
Glomma	0.138	-

4.2.1 Plots of all catchments

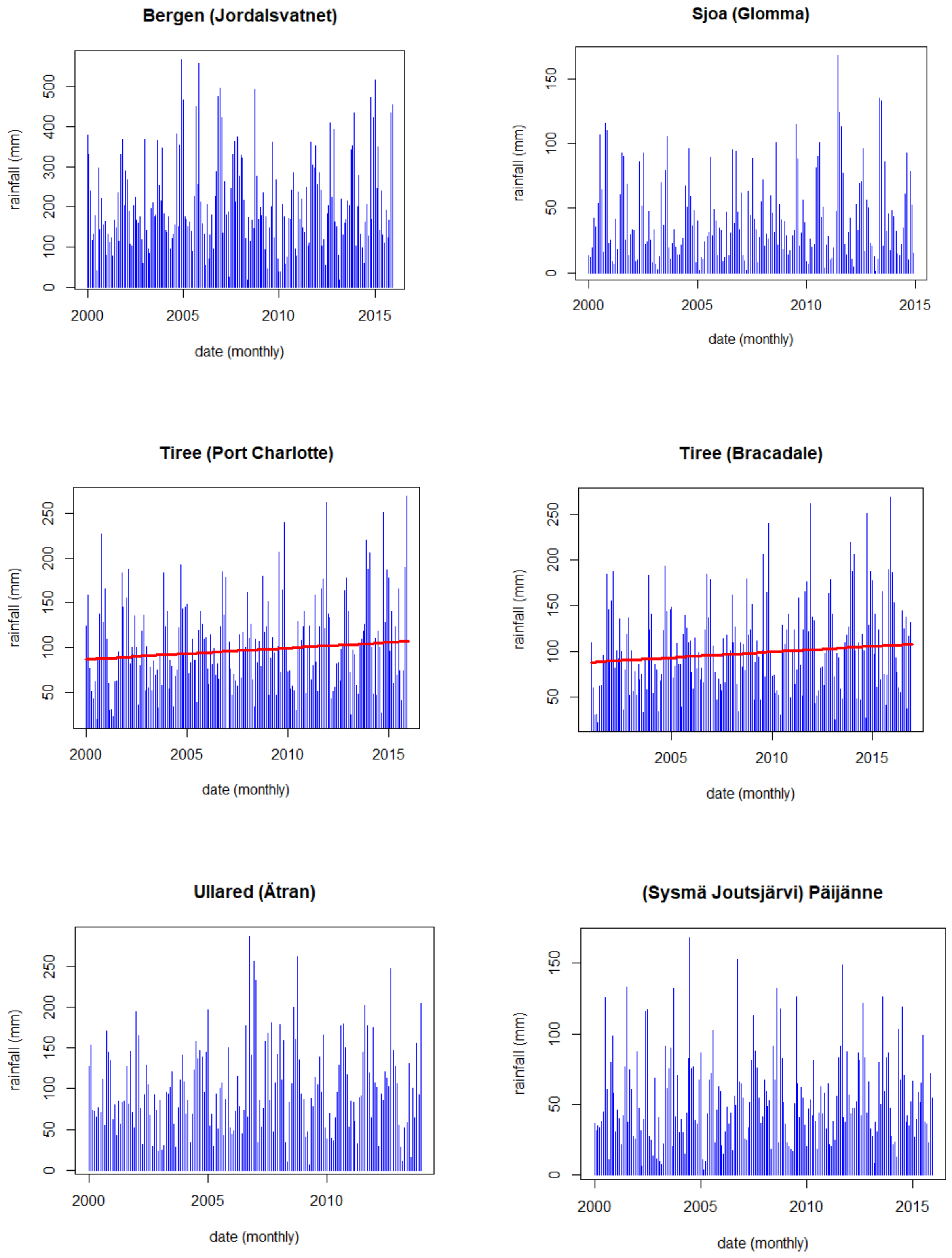

Figure 4.2-1. Plots of rainfall against date for the six catchments.

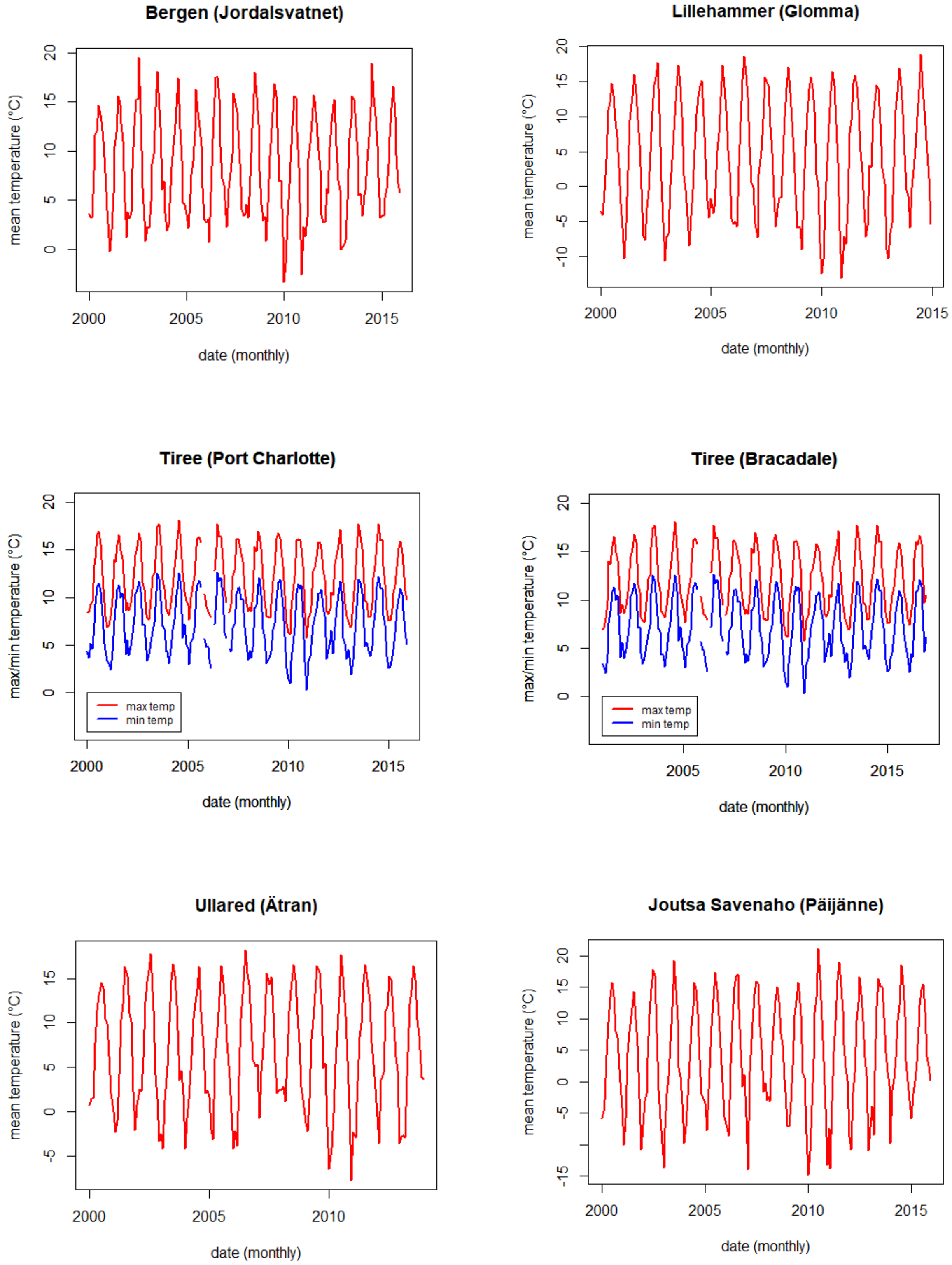

Figure 4.2-2. Plots of temperature against date for the six catchments.

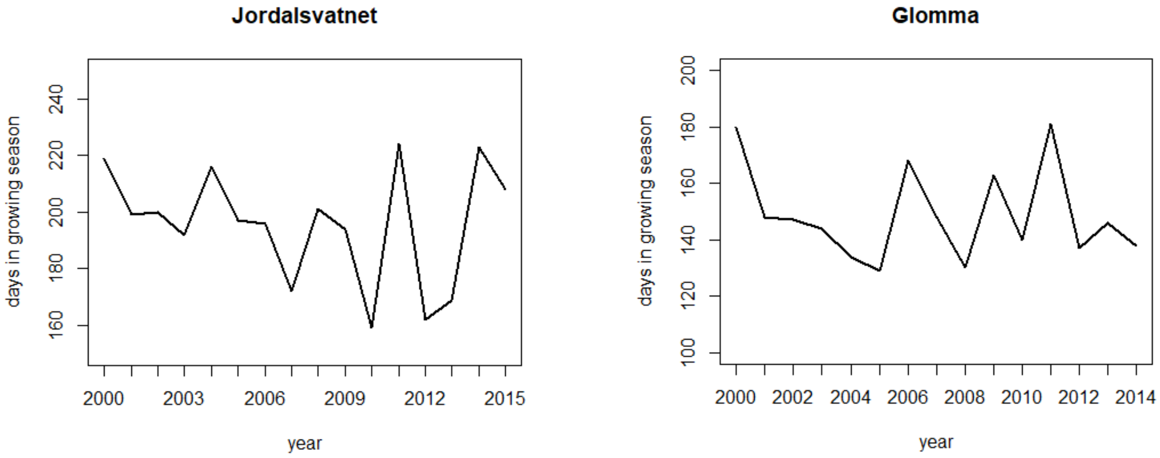

Figure 4.2-3. Plots of length of growing season for Jordalsvatnet and Glomma.

4.3 Time trends in NDVI

The Theil-Sen model suggests a significant increase in NDVI in Glomma, Port Charlotte and Päijänne. Päijänne has the highest increase in biomass, as well as the highest significance level. The overall NDVI results are given in Table 4.3-1. The slopes are given with four decimals, in order to easier compare the magnitude of the effects. Plots of NDVI against year are shown in Figure 4.3-1.

Table 4.3-1. Computed p-values for the effect of year in linear regression models and Theil-Sen (TS) estimators for the variable NDVI. The slopes are also included for the models where the change is statistically significant to a 95 % ($p < 0.05$) level. A slope field containing "-" means that the change is not statistically significant.
Catchments Jordalsvatnet and Glomma are defined by.shp files derived from NVE map services, while Ätran are defined by .shp files derived from VISS.
**:Slightly not statistically significant.*

Catchment	p-value linear regression	Multiple R^2 linear regression (adjusted R^2)	Change y^{-1} NDVI linear regression	p-value TS	Change y^{-1} NDVI TS
Jordalsvatnet	0.896	0.001 (-0.065)	-	0.854	-
Glomma	0.380	0.056 (-0.012)	-	0.037	0.0016
Port Charlotte	0.202	0.106 (0.046)	-	0.014	0.0019
Bracadale	0.340	0.061 (-0.002)	-	0.055*	0.0010
Ätran	0.454	0.044 (-0.030)	-	0.107	-
Päijänne	0.002	0.494 (0.458)	0.0041	0	0.0042

4.3.1 Plots of all catchments

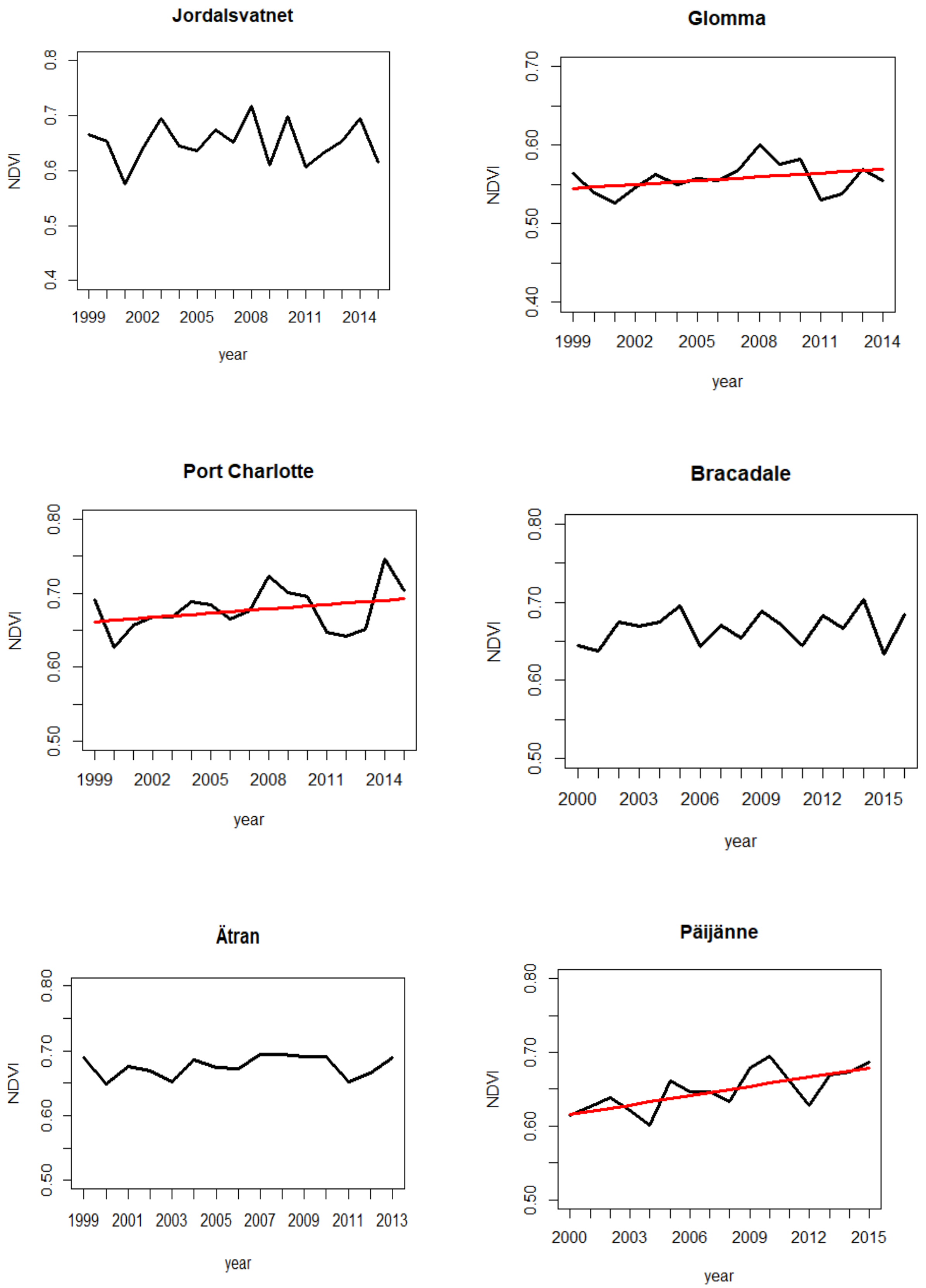

Figure 4.3-1. Plots of mean NDVI values against year for the six catchments. The fitted Theil-Sen estimators are included for the sites where this estimator is statistically significant.

4.4 Time trends in acid deposition

All catchments experienced a decline in acid deposition during the studied period. Jordalsvatnet in western Norway had by far the largest decrease, with about twice as large annual sulphate reduction than Ätran, with the second largest decrease. The smallest reductions in sulphate deposition were found in Glomma and Päijänne, approximately nine and eight times smaller than in Jordalsvatnet, respectively. Table 4.4-1 and Table 4.4-2 presents the change in acid deposition estimated by a linear regression model and a Theil-Sen estimator, respectively. The mean annual acid deposition at all sites are shown in Table 4.4-3. The plots of acid deposition against year are shown in Figure 4.4-1.

One characteristic of the sulphate deposition is that the level in 2014 is typically higher than the proceeding and the subsequent years. This is likely related to the volcanic eruption of Islandic Bardarbunga this year (Miljødirektoratet, 2020). The phenomenon is especially seen in the Norwegian catchments.

Table 4.4-1. Annual change in sulphate and in nitrate fitted by a linear regression model, with associated p-values and adjusted R^2. Catchments Port Charlotte, Bracadale and Päijänne is defined by a square represented by coordinates of its corners.
Jordalsvatnet and Glomma are defined by.shp files derived from NVE map services, while Ätran are defined by .shp files derived from VISS.

Catchment	**Change mg m^{-2} y^{-1} sulphate**	**p-value sulphate**	**Multiple R^2 (adjusted)**	**Change mg m^{-2} y^{-1} nitrate**	**p-value nitrate**	**Multiple R^2 (adjusted)**
Jordalsvatnet 2000-2015	-43.5	0.000	0.764 (0.747)	-23.1	0.000	0.597 (0.569)
Glomma 2000-2014	-5.86	0.001	0.581 (0.549)	-4.63	0.004	0.486 (0.447)
Port Charlotte 2000-2015	-18.2	0.000	0.847 (0.836)	-10.9	0.000	0.799 (0.785)
Bracadale 2001-2016	-12.6	0.000	0.803 (0.789)	-10.8	0.000	0.728 (0.708)
Ätran 2000-2013	-24.6	0.000	0.893 (0.884)	-17.6	0.000	0.616 (0.584)
Päijänne 2001-2015	-6.57	0.000	0.649 (0.622)	-3.32	0.012	0.396 (0.350)

Table 4.4-2. Annual change in sulphate and in nitrate fitted by a Theil-Sen estimator, with associated p-values.

Catchment	Change mg m^{-2} y^{-1} sulphate	p-value sulphate	Change mg m^{-2} y^{-1} nitrate	p-value nitrate
Jordalsvatnet	-46.6	0.000	-25.0	0.000
Glomma	-5.08	0.000	-3.23	0.000
Port Charlotte	-17.7	0.000	-10.4	0.000
Bracadale	-12.9	0.000	-9.90	0.000
Ätran	-22.8	0.000	-15.1	0.000
Päijänne	-6.20	0.000	-3.08	0.000

Table 4.4-3. Mean annual deposition of sulphate and nitrate through the time period studied for each catchment.

Catchment	Mean deposition sulphate mg m^{-2} y^{-1}	Mean deposition nitrate mg m^{-2} y^{-1}
Jordalsvatnet	751	997
Glomma	100	172
Port Charlotte	273	259
Bracadale	222	233
Ätran	341	609
Päijänne	144	183

4.4.1 Plots of all catchments

Figure 4.4-1. Plots of sulphate and nitrate deposition against year for the six catchments, with the curve of the Theil-Sen estimator. All sites experienced a statistically significant change in both sulphate and nitrate deposition.

4.5 Linear models of DOM against climate data

The linear regression model suggest a significant relationship between colour and rainfall in Jordalsvatnet, Port Charlotte and Ätran. The suggested strongest effect is in Ätran, about twice as strong as in Port Charlotte. The squared correlation coefficients are all relatively low. The largest is in Ätran where the linear model explains almost 11 % of the variation. The characteristics of the rainfall models are shown in Table 4.5-1.

A significant relationship between colour and temperature was found in Jordalsvatnet, Port Charlotte and Bracadale. The model for Jordalsvatnet suggests a relatively small effect, while the magnitude of the temperature effect is largest in Port Charlotte and Bracadale. The characteristics of the temperature models are shown in Table 4.5-2.

The plots of colour against rainfall and temperature are shown in Figure 4.5-1 and Figure 4.5-2, respectively.

Table 4.5-1. Computed p-values for the effect of rainfall on colour in linear regression models, along with multiple R^2 and adjusted R^2. The slopes are also included for the models where the change is statistically significant to a 95 % ($p < 0.05$) level. A slope field containing "-" means that the change is not statistically significant.

Catchment	**p-value**	**Multiple R^2 (adjusted R^2)**	**Change mg Pt l^{-1} mm^{-1}**
Jordalsvatnet colour	0.026	0.009 (0.007)	0.004
Glomma colour	0.330	0.002 (0.000)	-
Port Charlotte colour	0.000	0.052 (0.048)	0.261
Bracadale colour	0.368	0.003 (0.001)	-
Ätran colour	0.003	0.109 (0.098)	0.578
Päijänne colour	0.424	0.011 (-0.006)	-

Table 4.5-2. Computed p-values for the effect of temperature on colour in linear regression models, along with multiple R^2 and adjusted R^2. The slopes are also included for the models where the change is statistically significant to a 95 % ($p < 0.05$) level. A slope field containing "-" means that the change is not statistically significant.

Catchment	**p-value**	**Multiple R^2 (adjusted R^2)**	**Change mg Pt l^{-1} K^{-1}**
Jordalsvatnet colour	0.000	0.230 (0.229)	-0.409
Glomma colour	0.588	0.001 (-0.001)	-
Port Charlotte colour	0.000	0.139 (0.136)	6.175
Bracadale colour	0.000	0.330 (0.328)	8.701
Ätran colour	0.302	0.014 (0.001)	-
Päijänne colour	0.339	0.018 (-0.001)	-

4.5.1 Plots of all catchments

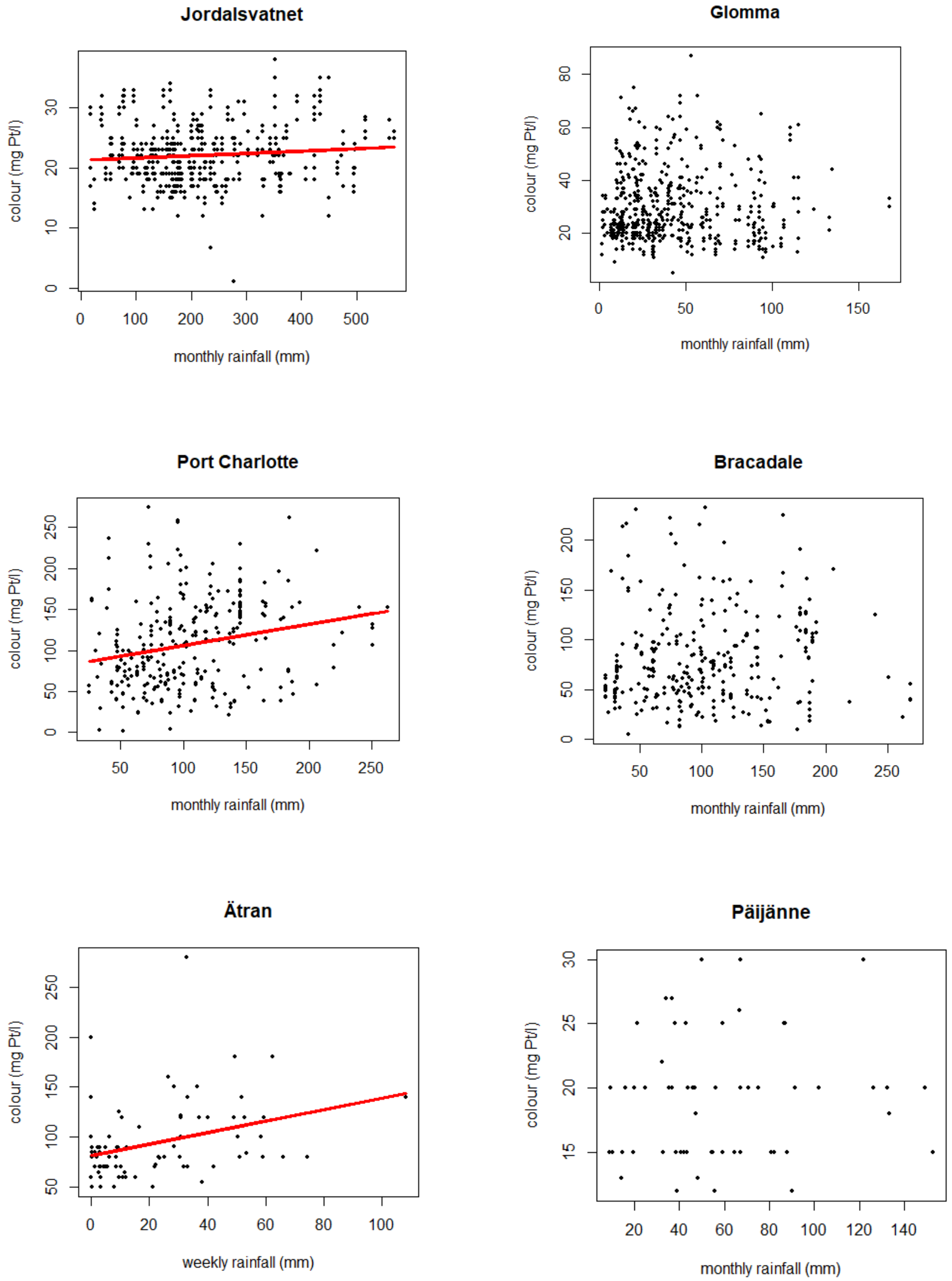

Figure 4.5-1. Plots of colour against rainfall for the six catchments. At the sites were a significant trend was found, the trend line is shown.

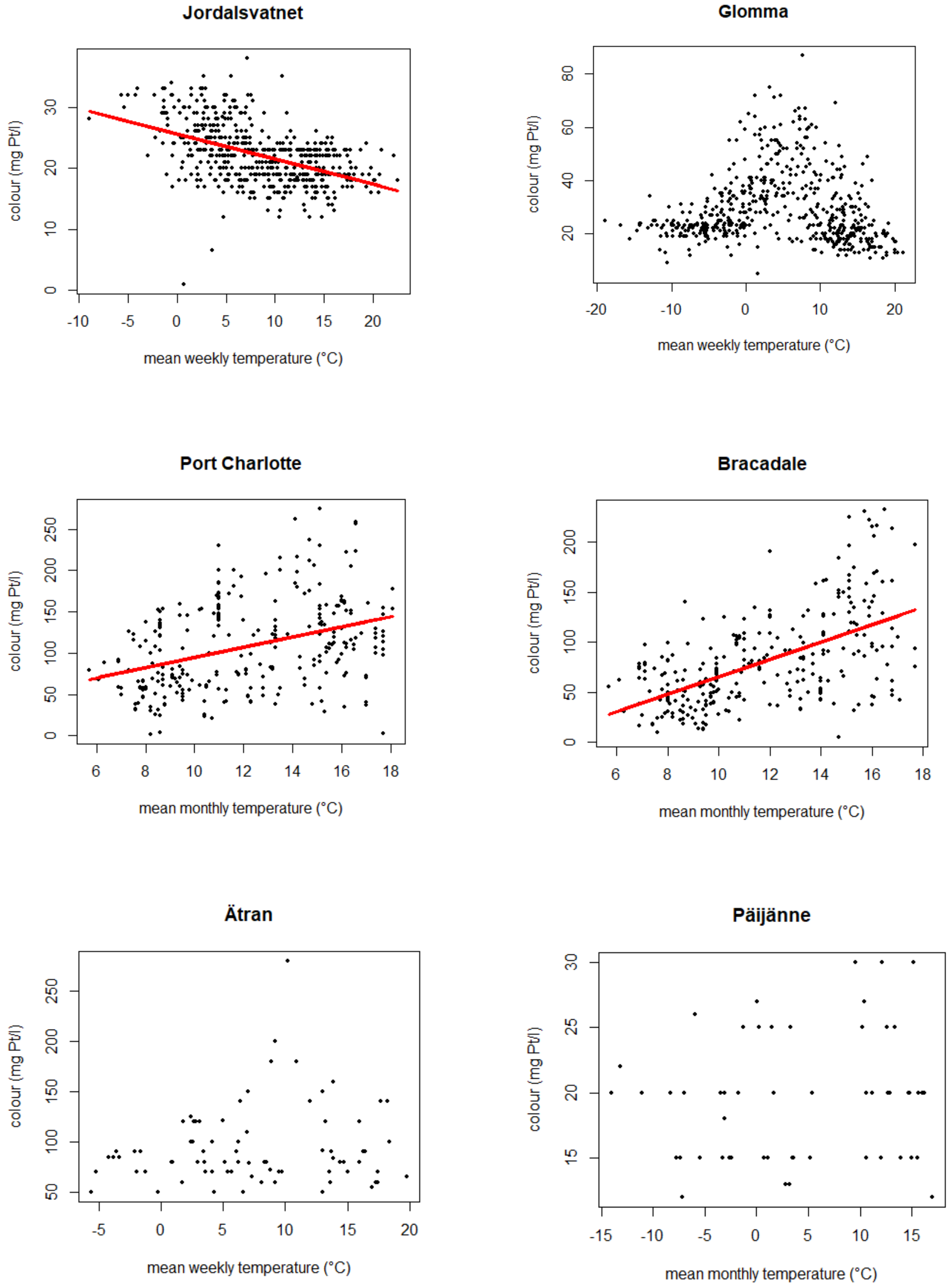

Figure 4.5-2. Plots of colour against temperature for the six catchments. At the sites were a significant trend was found, the trend line is shown.

4.6 Multivariate assessments

The plots of the principal component analyses (PCA´s) for the catchments are presented in subsections for each catchment. The loadings of all five principal components in the six PCS´s are given in Appendix F Results of PCA.

4.6.1 Jordalsvatnet

The biplot of the parameter loadings and sample component scores along the two first principal components (PC1 & PC2) in the PCA of yearly average data from Jordalsvatnet are shown in Figure 4.6-1. They explain 41 % and 29 %, respectively, (totally 70 %) of the variation.

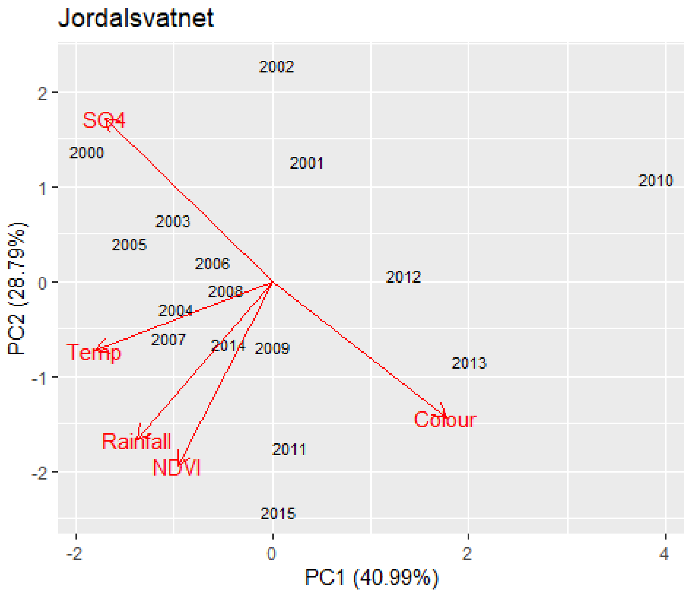

Figure 4.6-1. Biplot of the parameter loading and sample scores along the first and second principal components (PC1 & PC2) from the PCA of annual observations for Jordalsvatnet. Sample scores for each year are denoted with the year. The x- and y-axis are the sample scores of the first and second principal component, respectively. The axes of the parameter loadings are not shown.

4.6.2 Glomma

The biplot of the parameter loadings and sample component scores along the two first principal components (PC1 & PC2) in the PCA of yearly average data from Glomma are shown in Figure 4.6-2. They explain 33 % and 28 %, respectively, (totally 61 %) of the variation.

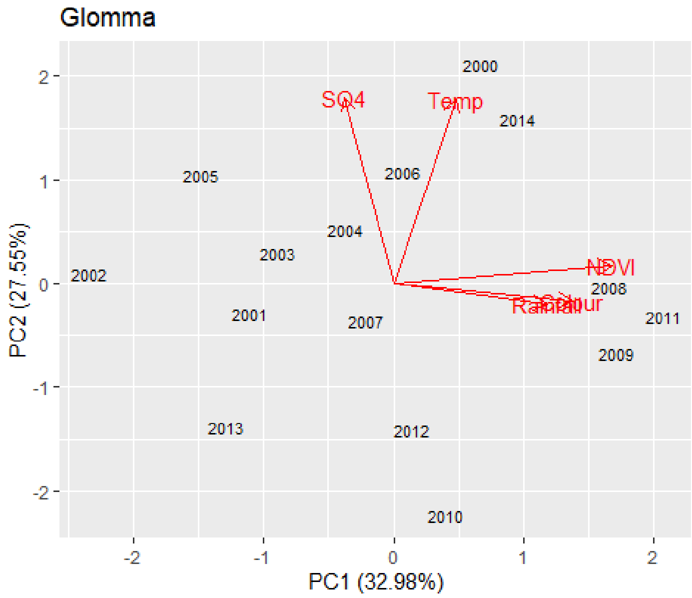

Figure 4.6-2. Biplot of the parameter loading and sample scores along the first and second principal components (PC1 & PC2) from the PCA of annual observations for Glomma. Sample scores for each year are denoted with the year. The x- and y-axis are the sample scores of the first and second principal component, respectively. The axes of the parameter loadings are not shown.

4.6.3 Port Charlotte

The biplot of the parameter loadings and sample component scores along the two first principal components (PC1 & PC2) in the PCA of yearly average data from Port Charlotte are shown in Figure 4.6-3. They explain 34 % and 26 %, respectively, (totally 60 %) of the variation. Only the maximum temperature was included, as the Pearson correlation between the maximum and minimum temperature was high (r = 0.978, Appendix D Pearson correlations).

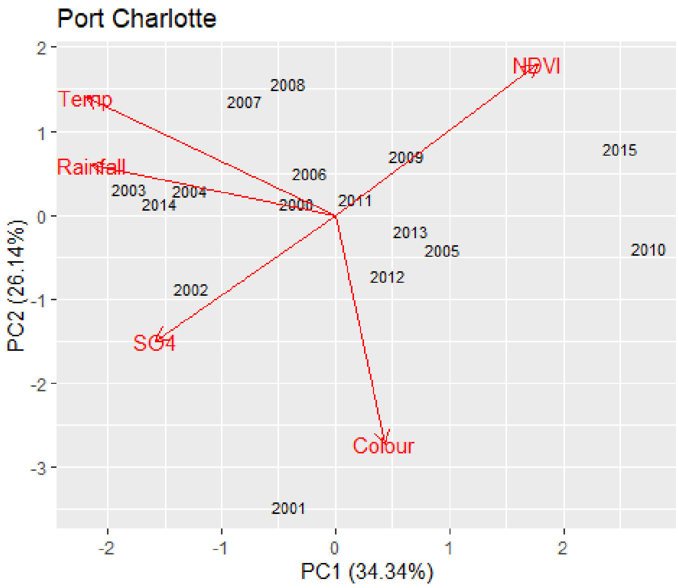

Figure 4.6-3. Biplot of the parameter loading and sample scores along the first and second principal components (PC1 & PC2) from the PCA of annual observations for Port Charlotte. Sample scores for each year are denoted with the year. The x- and y-axis are the sample scores of the first and second principal component, respectively. The axes of the parameter loadings are not shown.

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4.6.4 Bracadale

The biplot of the parameter loadings and sample component scores along the two first principal components (PC1 & PC2) in the PCA of yearly average data from Bracadale are shown in Figure 4.6-4. They explain 39 % and 24 %, respectively, (totally 63 %) of the variation. As for Port Charlotte, only the maximum temperatures were included, as the Pearson correlation between the maximum and minimum temperature was high (r = 0.978, Appendix D Pearson correlations).

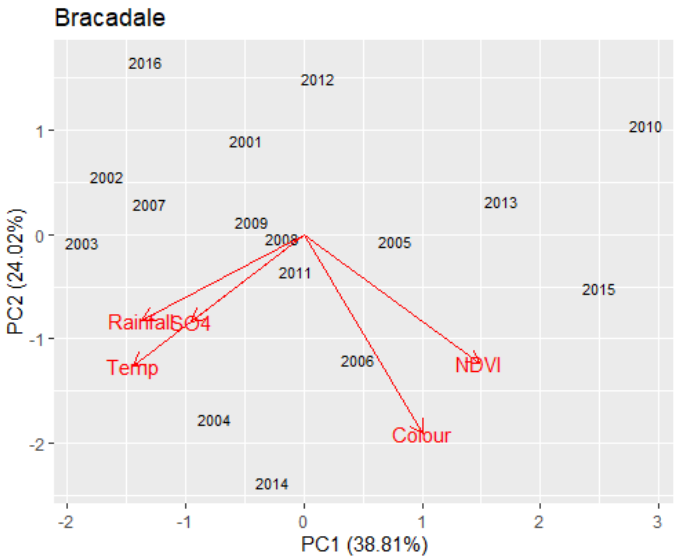

Figure 4.6-4. Biplot of the parameter loading and sample scores along the first and second principal components (PC1 & PC2) from the PCA of annual observations for Bracadale. Sample scores for each year are denoted with the year. The x- and y-axis are the sample scores of the first and second principal component, respectively. The axes of the parameter loadings are not shown.

4.6.5 Ätran

The biplot of the parameter loadings and sample component scores along the two first principal components (PC1 & PC2) in the PCA of yearly average data from Ätran are shown in Figure 4.6-5. They explain 42 % and 25 %, respectively, (totally 67 %) of the variation.

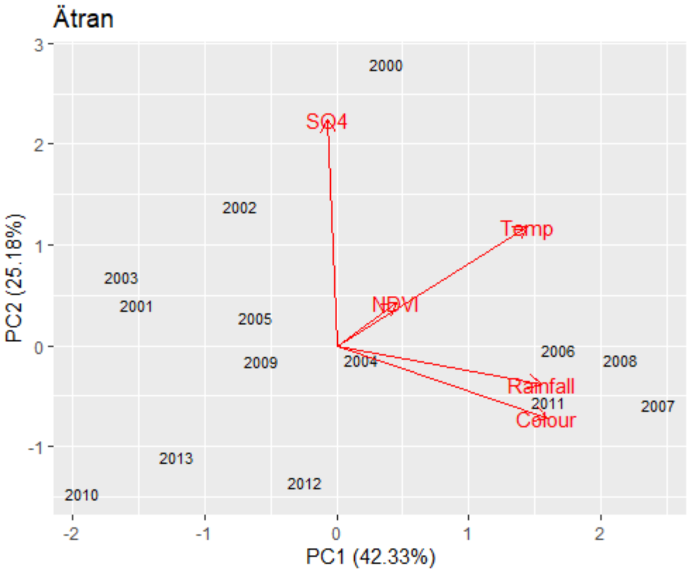

Figure 4.6-5. Biplot of the parameter loading and sample scores along the first and second principal components (PC1 & PC2) from the PCA of annual observations for Ätran. Sample scores for each year are denoted with the year. The x- and y-axis are the sample scores of the first and second principal component, respectively. The axes of the parameter loadings are not shown.

4.6.6 Päijänne

The biplot of the parameter loadings and sample component scores along the two first principal components (PC1 & PC2) in the PCA of yearly average data from Päijänne are shown in Figure 4.6-6. They explain 45 % and 20 %, respectively, (totally 65 %) of the variation.

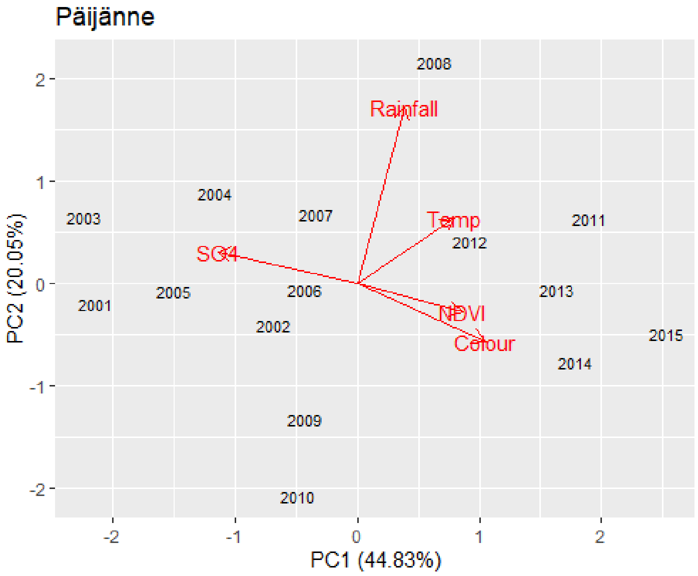

Figure 4.6-6. Biplot of the parameter loading and sample scores along the first and second principal components (PC1 & PC2) from the PCA of annual observations for Päijänne. Sample scores for each year are denoted with the year. The x- and y-axis are the sample scores of the first and second principal component, respectively. The axes of the parameter loadings are not shown.

5 Discussion

5.1 Introduction to discussion

In this chapter, first the results from the principal component analyses are discussed together with the results of the linear regression models with climate parameters and colour (5.2). The results from the key findings in the time trend analyses are also included in the discussion of the PCA´s. Furthermore, a summarizing discussion of the three drivers (5.3), taking all the analyses as well as the characteristics of the catchments into account, is given.

It is beneficial to have an overview of the key findings in the data to start a discussion. Table *5.1-1* shows the results of time trend analyses for the various variables, for the six catchments. Furthermore, Table *5.1-2* summarizes the results of the PCA´s as well as the models of DOM as against climate parameters.

Table 5.1-1. Site specific trends in TOC, colour, precipitation, air temperature, NDVI, sulphate and nitrate deposition. A field denoted with "-" means that this variable is not given for this catchment. A field containing "-" means that the trend is not statistically significant.
*Slightly not significant

Catchment	**Assessed Period**	**TOC** mg l^{-1} y^{-1}	**Colour** mg Pt l^{-1} y^{-1}	**Rainfall** mm^{-1} y^{-1}	**Temp.** K^{-1}	**NDVI y^{-1}**	**Sulphate** mg m^{-2} y^{-1}
Jordalsvatnet	2000-2015	Not observed	+0.46	-	-	-	-46.6
Glomma	2000-2014	-	-	-	-	+0.0016	-5.08
Port Charlotte	2000-2015	Not observed	-	+1.26*	-	+0.0019	-17.7
Bracadale	2001-2016	Not observed	+0.96	+1.24*	-	+0.0001	-12.9
Ätran	2000-2013	+0.25	+0.91*	-	-	-	-22.8
Päijänne	2001-2015	+0.17	+1.00	-	-	+0.0042	-6.20

Table 5.1-2. Slope of linear trends of colour against climate parameters for the six catchments (left). Fields denoted with "-" means that the effect of this variable is not significant for this catchment. In addition, for the PCA´s, the variables with positive or negative correlation to colour are given, with prefix "+" or "-", respectively.

	Linear regression colour and climate parameter			**PCA**
Catchment	**Rainfall mg Pt L^{-1} mm^{-1}**	**Temp. mg Pt L^{-1} K^{-1}**		**Eigenvector direction with respect to colour**
Jordalsvatnet	+0.004	-0.409		- Sulphate
Glomma	-	-		+ NDVI + Rainfall
Port Charlotte	+0.261	+6.170		- Rainfall - Temperature
Bracadale	-	+8.700		+ NDVI
Ätran	0.578	-		+ Rainfall
Päijänne	-	-		+ NDVI - Sulphate

5.2 Combined discussion of time trend, PCA and linear regression for each catchment

Summed up, the PCA of the various catchments often, but not always, emphasized what the trend analysis already suggested. Variables having a governing effect on DOM, independent of experiencing any long-term trend, appear in the PCA plot in the same or opposite direction of the "Colour" response parameter. Moreover, the analyses are characterized by challenges related to seasonality. The yearly averaging of colour, temperature and rainfall observations leads to a simplified description of the data, where the seasonal aspect is lost.

The linear regression models provide additional information about the data, though it is important to discuss potential dependencies to other variables when interpreting these correlations. Among the rainfall models, the model for Ätran had the highest coefficient of determination, explaining almost 11 % of the variation. The rainfall model for Port Charlotte explains about 5 % of the variation, and the remaining rainfall models less than 1 %. The relative low values of R^2 can seem surprising due to that there is a known mechanistic relationship between precipitation and DOM (Chapt. 2.7). However, the low correlations can be a result of that monthly observations for precipitation is a too poor resolution, except from Ätran (with the highest correlation), where the recent seven days were used. The models with temperature as predictor have generally higher R^2.

5.2.1 Jordalsvatnet

Based on the time trend in DOM (4.1) there is a significant, though slight increase in colour (0.46 mg Pt/L yr^{-1}) from the start to the end of the period. This indicates that there has been a change in the governing variables during the period. In the biplot of PC1 and PC2 from the PCA of the average yearly data from Jordalsvatnet (Figure 4.6-1) the sulphate deposition has a strong negative loading to colour. The other explanatory variables form a 90° angle to the colour through the origin of the plot, implying that they have no explanatory value for the changes in colour in the PC1 and PC2 plane, explaining 70% of the variation in the data. This clearly emphasizes that the most significant governing factor for the increasing time trend in DOM is the decrease in acid rain.

The linear regression model, explaining less than 1% of the variance, suggest that increased rainfall has a slight increasing effect on DOM. This is the contradictory to the findings in the NOMiNOR project, that suggests that due to thin soil there will be a dilution effect of increased precipitation (Eikebrokk et al., 2018a). Apparently, changes in waterways, increasing the DOM at high runoff, is also taking place in the watershed of Jordalsvatnet. There is no long-term time trend in precipitation (4.2). This correlation therefore only reflects the effect of precipitation on the seasonal fluctuation in DOM. Nevertheless, the change in DOM with change in precipitation is practically insignificant.

DOM decreases substantially with temperature since the mean colour is highest in the winter, when the temperature is lowest. It is conceivable that this has to do with the fact that in the winter there may be an up-concentration of DOM due to that the precipitation that comes is partly in the form of snow on the very thin soils with little groundwater.

5.2.2 Glomma

In the Glomma river there is no long-term change in DOM (4.1), despite a significant long-term increase in biomass (Table 4.3-1) and decrease in acid rain (Table 4.4-1) in the watershed. There are also no significant long-term trends in climate parameters. The PCA biplot (Figure 4.6-2) indicates that yearly rainfall and biomass (NDVI) are important drivers for the year to year fluctuation in DOM, as their eigenvectors are parallel. The significant long-term reduction in acid deposition has no apparent effects on DOM. That rainfall has an explanatory value, despite any apparent seasonal correlation to DOM (4.5) may be due to that the year to year variation in rainfall is correlated to DOM. That the significant reduction in acid rain is not influencing the DOM is likely due to the large contribution of groundwater to this large high order river.

The linear regression with climate variables gave no significant relationships. The catchment thus appears to be less responsive to changes in temperature and precipitation. This is likely mainly due to that the catchment is large and complex, the river is a high order stream, and thus has a substantial contribution of groundwater. Nevertheless, the colour fluctuates with seasons, peaking in the spring and fall. Thus, the seasons with extreme temperature values (i.e., winter and summer) are associated with generally lower DOM concentrations, and the seasons with intermediate temperature values (i.e., spring and fall) are associated with generally higher DOM concentration. The overall result is that there is no linear trend. Furthermore, the highest precipitation amounts in the Glomma watershed are in the summer, followed by the fall. There is also a significant water flux during the late spring and early summer due to mountain snowmelt causing low colour concentrations, when the precipitation is at its highest. It is thus not surprising that there is no linear relationship between rainfall and colour in this large watershed. The snowmelt during late spring and summer is an important factor that is not reflected by the rainfall parameter. However, snowmelt can lead to comprehensive runoff and hence dilution of DOM, possibly contributing to the low colour values in the summer.

5.2.3 Port Charlotte

The time trend analysis of the DOM data from Port Charlotte indicates that there has not been a long-term trend in DOM (4.1). Thus, the PCA may enhance the understanding of which factors are important for explaining variations in DOM in a year-to-year perspective. As sulphate and NDVI are approximately normally oriented with regards to DOM in the PC1 vs. PC2 plot, they have small impacts on DOM. However, the PCA shows that temperature and rainfall has a strong negative loading to colour and is thus important in governing the year-to-year variation in DOM. This analysis suggests that lower temperatures and precipitation amounts results in more DOM in the Port Charlotte runoff.

There is no significant long-term trend in temperature, though there is almost a significant ($p=0.07$) increase in precipitation. The linear model gives a significant positive correlation between DOM and temperature, and between DOM and rainfall ($p < 0.05$, 4.5). These correlations are likely mainly due to seasonal variations. The highest concentrations of DOM are in the fall and in the summer, where relatively higher temperatures also are typically observed. The explanatory value of temperature is not high (14%), but can perhaps be explained by an increased biological degradation of SOM and thereby production of DOM in the summer. We find this again in the PCA plot where Temp has a negative loading to Colour. The seasonal fluctuation in amount of precipitation is basically the opposite of the temperature, with lowest in late spring and early summer and highest in the late fall and early winter (Met Office, 2021).

It is clear that the seasonal and year-to-year variation in the amount of precipitation and temperature are important in governing the variation in DOM at Port Charlotte, though the response mechanisms are not clear. Seasonally, these drivers are positive correlated to DOM, though on a year-to-year basis they are negatively loaded. This is likely linked to the opposite seasonal fluctuations of temperature and precipitation.

5.2.4 Bracadale

The PCA indicates that the significant ($p < 0.05$, 4.1) increase in DOM is mainly driven by the slightly significant increase in biomass ($p = 0.06$, 4.3) in Bracadale, as the eigenvector of these two variables in the PCA are relatively similar. The parameters sulphate deposition, temperature and rainfall do not seem to have an impact on DOM, even though there is a significant decrease in acid rain ($p < 0.05$, 4.4) and a slightly significant ($p = 0.06$, 4.2) increase in rainfall.

The linear regression model suggests that there is no relationship between colour and rainfall (4.5). This follows the indication from the PCA, saying that colour and rainfall are not correlated. On the other hand, the linear correlation model suggests that higher DOM levels are associated with higher temperatures. Hence, this relationship is similar to Port Charlotte. It may be surprising that there is a significant correlation between rainfall and colour only in Port Charlotte, while there is a significant correlation between temperature and colour in both sites, when the same climate data is used. However, for Port Charlotte, the model with temperature has a statistical significance level more than 10^7 times higher than the model with rainfall has. Hence, the model using rainfall is more sensitive to changes in colour observations.

5.2.5 Ätran

In Ätran there was a slightly significant ($p = 0.06$, 4.1) long-term increase in colour and a significant ($p < 0.05$) increase in TOC. Based on the linear regression model, rainfall has a significant ($p < 0.05$) impact on colour though it only explains almost 11 % of the variance in colour. In the PCA of the yearly average data the colour is closely clustered with rainfall. Hence, high DOM concentrations are typically seen in years with high precipitation amounts, though there has been no significant long-term trends in the precipitation amount. As colour and rainfall have relatively high loadings as well, they must be important for explaining the total variation. However, the observations appears randomly plotted with regards to colour and rainfall, and rainfall therefore only explains the year-to-year variation. The clearest long-term trend at Ätran is the decrease in sulphate deposition. In the PCA biplot the sample scores from earlier years are typically situated close to the sulphate loading, while later observations are found on the opposite side, close to the loading of colour. However, its eigenvector is close to normally oriented to the colour eigenvector, indicating that these are weakly correlated. That the decline in acid rain seems to have small impact on DOM may be due to that the river is limed and that at least part of the catchment has soils that contain carbonate minerals.

The linear regression model fitting colour as a function of rainfall suggests a significant increase in DOM with increasing precipitation. This may therefore explain the seasonal fluctuation as well as the year-to-year variation. The mean precipitation amount is highest in the fall, followed by the winter, the summer and the spring. This sequence is the same for mean colour. For temperature, the correlation is far from significant, and temperature seems to have small effects on DOM concentration in Ätran, in any timescale.

5.2.6 Päijänne

There is a significant ($p < 0.05$, 4.1) and strong increase in DOM over time in Päijänne, both in regards to colour (1.00 mg Pt/L yr^{-1}) and TOC (0.17 mg C/L yr^{-1}). There is a significant long-term increase in NDVI and decrease in acid rain, while there are no long-term trends in the climate parameters. The sample scores in the PC1 and PC2 biplot of the PCA are relatively clearly separated. Later years are typically found with high positive scores on the PC1 along with high loading of colour and NDVI, while samples from earlier years are found with high negative scores on the PC1 along with high negative loading of sulphate. Hence, this analysis indicates clearly that the significant increase in DOM is driven by both the significant increase in biomass and the significant decline in acid rain. In addition, the reduction in chlorides in the lake water due to closing of the local paper industry (Eikebrokk et al., 2018a), decreases the ionic strength, which increases the solubility of DOM. Hence, this additional mechanism, together with the increase in biomass and reduction in acid rain have likely been the governing factors for DOM increase in Päijänne.

5.3 Discussion of parameters

5.3.1 Climate change as governing factor for increase in DOM

There were no clearly significant long-term changes in the climatic factors rainfall and temperature at the sites studied, though there were large seasonal fluctuations and variations from year to year. DOM concentrations fluctuate with temperature and precipitation within each year to various extent in different catchments, but they do not appear to be the main drivers behind the four cases of significant DOM increase assessed in this study. At Port Charlotte and in Glomma, having no long-term trend in DOM, the year-to-year variation in DOM was partly governed by the variation in precipitation amount, although there is no significant correlation between precipitation amount and colour in Glomma. Nevertheless, wet years have higher DOM levels in Glomma due to more sub-lateral flow through till soils. At Port Charlotte, an increase in rain on the prevalence of water saturated peats causes an overall greater dilution and thus a decline in DOM. At Port Charlotte the variation in temperature was also important in explaining the year to year DOM variation. In Ätran the significant increase in DOM appear from the PCA to be explained by an increase in rainfall, similar to Glomma, although there is no long-term trends in precipitation.

5.3.2 NDVI as governing factor for increase in DOM

Päijänne had the largest significant increase in NDVI, more than twice as large as Port Charlotte and Glomma, with the second and third largest increases, respectively, and four times that at Bracadale. In the PCA the increase in NDVI had a strong explanatory value for the increase in DOM at Päijänne, Glomma and Bracadale. No long-term trend in DOM at Port Charlotte, despite a significant and strong increase in NDVI and decrease in acid rain, may be due to the slightly insignificant increase in precipitation diluting the DOM concentration. Päijanne had small reductions in acid deposition, thus the increase in biomass is likely an important driver for increased DOM concentration over the period studied.

5.3.3 Acid deposition as governing factor for increase in DOM

Even though the main decrease in SO_2 and NOx emission were in the 80´s and 90´s the deposition of acid rain was significantly reduced during the study period at all the six catchments. Nevertheless, the decrease in sulphate had only a strong explanatory value in the PC1 vs. PC2 plane for Jordalsvatnet and Päijänne. Jordalsvatnet has by far had the largest decrease in acid rain, while there has been no significant change in climate and biomass. Due to the dominance of igneous silicate-based rocks, the soil in Jordalsvatnet is sensitive to this reduction in acid rain which thus have resulted in elevated levels of DOM. Considering Glomma, the magnitude of the decline in acid rain is less than in for example Jordalsvatnet, about 10.1 and 6.6 times smaller for sulphate and nitrate deposition, respectively. Hence, the *amount* of acid deposition may play an important role, not just whether there has been a change or not. The strength of the declining trend of acid deposition in Glomma is similar to Päijänne. However, the Finnish site had a rise in DOM, but here the net biomass increase may explain most of the elevated DOM amounts.

Since the soil at Bracadale contains substantial amounts of carbonates and magnesium, the effect the decline in acid rain has on reducing ionic strength is limited. This means that the relative importance of biomass increase is higher. Hence, the rise in NDVI may have greater effect in Bracadale than in Päijänne even though both sites experience similar decrease in acid deposition. At Port Charlotte there was a significant decrease in acid deposition, as well as a rise in NDVI and rainfall. Although increased biomass and decreased acid deposition are clear drivers of increased DOM, the concurrent increased precipitation on these already water logged organic peat soils has apparently buffered the effect causing no significant long-term increase in DOM. On the other hand, Bracadale has experienced elevated DOM concentrations, even with weaker effects of rainfall, NDVI and acid rain. This striking difference in response between Port Charlotte and Bracadale despite inherently similar regional drivers must be due to their local differences in edaphic conditions. As explained above, due to more peaty soils at Port Charlotte, the dilution effect of increased precipitation may have counterweighted the effect of increased sub-lateral flow and decline in acid deposition.

5.3.4 Governing factors for DOM

At Jordalsvatnet the only significant long-term change in potential drivers of changes in DOM is the decrease in acid deposition. It is thus clear that the significant increase in DOM at this site must be due to this decrease in acid rain. The significant increase in colour in Bracadale appears to be mainly governed by the increase in biomass, although there has been an increase in rainfall that may have led to more sub-lateral flow through the soil into surface waters. The catchment area associated with the river Ätran is mostly above marine limit, meaning that a potential increase in ionic strength due to marine sediments is limited. However, this river has been limed, thus carbonates and base cations Ca^{2+} and Mg^{2+} have been added. Although Ätran experienced a significant decline in acid rain, the relative decrease in ionic strength is less when it is limed, due to already present high levels of bicarbonate base cations. When the acid deposition is reduced, the ionic strength is reduced, but the relative decrease is not so strong. This causes the solubility of DOM to increase, but no so much. Still, Ätran has one of the highest increases in DOM among the studied catchments. It is worth mentioning that Ätran has received the second largest yearly amounts of sulphate and had the second largest decline in sulphate in the period in focus, after Jordalsvatnet. Moreover, the general levels of colour in Ätran are more than 4 higher than in Jordalsvatnet, so a 2 times higher increase in colour in Ätran still means that the increase in percentage in colour is twice as high in Jordalsvatnet.

6 Conclusion

The year-to-year variation in DOM can often be explained by the climatic factors precipitation and temperature. Warmer years generally give more DOM. Precipitation is enhancing DOM concentrations in sites with till soils. In sites with water saturated peats an increase in rainfall amount can cause a greater dilution, resulting in reduced DOM concentration.

The reduction in acid deposition is the driver of elevated DOM levels in Jordalsvatnet, which has a soil characterized by igneous silicate-based rocks, being sensitive to the decline in acid rain. Furthermore, Ätran also seems to experience an increase in DOM due to decline in acid rain. In Bracadale and Päijänne, increase in biomass has probably been a main driver of rising DOM, along with the acid rain decline, to some extent. In addition, the closing of local paper industry in Päijänne has led to reduction in ionic strength, increasing DOM solubility. This is also a remainder of the importance of considering site-specific characteristics while studying this topic. Changes in biomass in Glomma seem to contribute to the variation in DOM concentration from year to year.

Port Charlotte had no significant change in DOM, although precipitation and biomass rose, as well as acid rain decreased. This may be because precipitation has a diluting effect, due to substantial cover of peatlands in the catchment site, counteracting the effect of more biomass and reduction of acid rain.

The seasonal effects of temperature and rainfall detected by the ordinary least squared method in linear regression, confirms that these effects are potential drivers for a long-term change. However, as few clear temporal trends in temperature nor rainfall were found, these have not played a key role in the sites in this study.

7 Further work

For further work within this field, it would have been beneficial to use climate data with a higher resolution, as daily observations. This provides better conditions for understanding the relationship between DOM and climate change. Moreover, more frequent observations of NDVI and acid deposition would have facilitated a stronger PCA. In this study, the colour variable was treated as the major proxy for DOM, while the TOC variable was barely mentioned, although they may experience quite different relative changes, as in Ätran. It would have been interesting if further studies focus more on how also TOC is affected by the various drivers. Finally, a more thoroughly examination and analysis of catchment characteristics should be done, such that mechanisms can be more entirely understood in association with these.

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9 List of appendices

9.1 Appendix A Locations of catchments

Appendix A provides the GPS coordinates of the catchments, used for extracting NDVI and acid deposition values I RStudio. These are shown in Table 9.1-1.

Table 9.1-1. Coordinates used in this thesis to represent the catchments in Scotland and Finland. Coordinates are given in WGS 84, as decimal coordinates.

Catchment	Latitude range (N°)	Longitude range (E°)
Port Charlotte	(55.748094, 55.762395)	(-6.431428, -6.405229)
Bracadale	(57.358378, 57.382873)	(-6.421298, -6.398836)
Päijänne	(60.932124226, 63.456476636)	(25.101002663, 27.174448549)

9.2 Appendix B Characteristics of driver´s data

In Appendix B the characteristics of the observations of various parameters analysed in this study are presented.

9.2.1 Rainfall

Table 9.2-1 gives an overview of the resolution of the observations of precipitation in the six sites. The entire datasets downloaded (raw data) from the databases are not included, due to space issues. The precipitation values after pre-processing the raw data for conducting linear regression analyses and principal component analyses are included in Appendix E Data used in R scripts.

Table 9.2-1. Overview of precipitation data characteristics for the six catchments.Notice that some dates are given as month in year (MY), others are given as day in month in year (DMY).

Catchment	Start date (MY/DMY)	Stop date (MY/DMY)	Resolution (frequency)	Comments
Jordalsvatnet	01.2000	12.2015	Monthly	
Glomma	01.2000	12.2014	Monthly	
Port Charlotte	01.2000	01.2021	Monthly	
Bracadale	01.2000	01.2021	Monthly	
Ätran	30.09.1995	31.12.2021	Daily	Precipitation amount from 06 AM to 06 AM the day after.
Päijänne	01.2000	12.2015	Monthly	

9.2.2 Temperature

Table 9.2-2 gives an overview of the resolution of the observations of temperature in the six sites. The entire datasets downloaded (raw data) from the databases are not included, due to space issues. The temperature values after pre-processing the raw data for conducting linear regression analyses and principal component analyses are included in Appendix E Data used in R scripts.

Table 9.2-2. Overview of temperature data characteristics for the six catchments.

Catchment	Start date (DMY)	Stop date (DMY)	Resolution (frequency)	Comments
Jordalsvatnet	01.01.1999	31.12.2015	Daily	Mean temperature
Glomma	01.01.2000	31.12.2014	Daily	Mean temperature
Port Charlotte	24.01.2000	13.10.2015	Monthly	Maximum and minimum temperature,
Bracadale	10.01.2001	09.05.2016	Monthly	Maximum and minimum temperature,

Ätran	30.09.1995	31.12.2021	Every hour	Instantaneous temperature
Päijänne	01.2000	12.2015	Monthly	Mean temperature

9.2.3 Acid deposition

Table 9.2-3 gives an overview of characteristics of the acid deposition data in the six sites. The acid deposition values are included in Appendix E Data used in R scripts.

Table 9.2-3. Overview of which years that are used in the analyses of sulphate and nitrate deposition in each catchment.

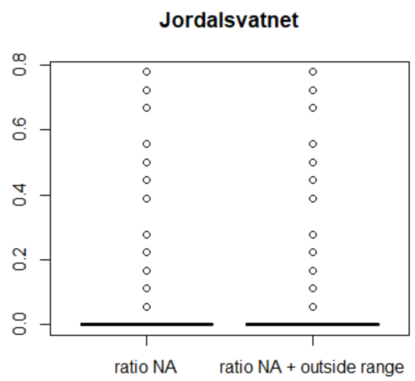
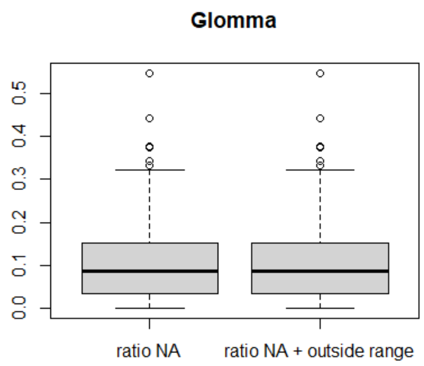
Catchment	Start year	Stop year	Comments
Jordalsvatnet	2000	2015	Shapefile used
Glomma	2000	2014	Shapefile used
Port Charlotte	2000	2015	Square defined by coordinates used
Bracadale	2001	2016	Square defined by coordinates used
Ätran	2000	2003	Shapefile used
Päijänne	2000	2015	Square defined by coordinates used

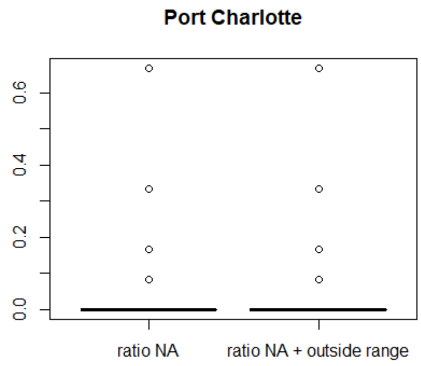
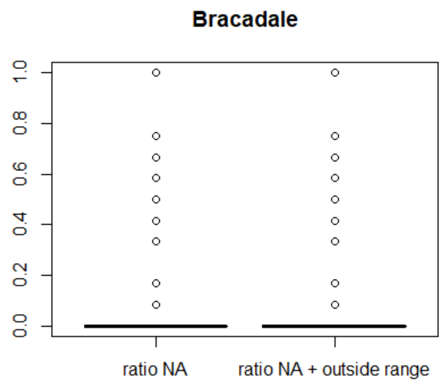
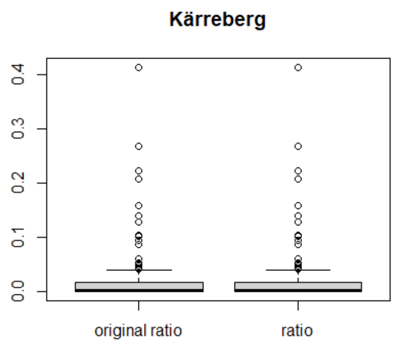
9.3 Appendix C NDVI data

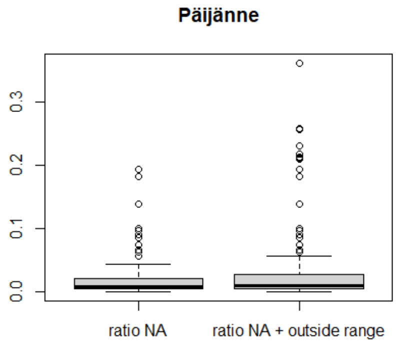
9.3.1 NA fraction of NDVI data

Table 9.3-1 shows boxplots of the ratio of NA values within the catchments.

Table 9.3-1. Overview of ratio of NDVI values that are NA values, for the six catchments. The time period for each catchment corresponds to the time range of which NDVI is studied. Each observation in the boxplot corresponds to one .nc file, and is the mean of all the observations within the catchment.
Explanation of the boxplots: Lines from bottom to top: Minimum that is not an outlier, first quartile (Q_1), median (second quartile), third quartile (Q_3), maximum that is not an outlier. The interquartile range (IQR) is the difference between the first and third quartile. An observation is considered an outlier if it is outside the range [Q_1 – 1.5IQR, Q_3 + 1.5IQR]. Outliers are shown as dots in the boxplots.

Catchment	Boxplot of ratio of NDVI values that take the value NA/NA or outside the range [-0.08, 0.92].	Comments
Jordalsvatnet **n = 153**		No difference between the two ratios. Thus all but 12 files consist of observations that are originally valid (Non-NA and within valid range).
Glomma **n = 144**		

Port Charlotte **n = 153**		No difference between the two ratios. Thus all but 4 files consist of observations that are originally valid (Non-NA and within valid range).
Bracadale **n = 153**		No difference between the two ratios. Thus all but 9 files consist of observations that are originally valid (Non-NA and within valid range).
Ätran **n = 135**		

Päijänne **n = 144**		Some difference between the two ratios. Thus, some observations are probably related to the very large lake surface. Except from outliers, both ratios are substantially below 0.1.

9.4 Appendix D Pearson correlations

Here the data for which Pearson correlations were computed is shown, along with the correlation coefficients.

9.4.1 DOM proxies correlations in Glomma, Ätran and Päijänne

Table 9.4-1 shows computed correlations between TOC and colour.

Table 9.4-1. Pearson correlation of TOC and colour for the catchments Glomma, Ätran and Päijänne.

Catchment	Correlation (*R*) TOC, colour
Glomma	0.8273224
Ätran	0.7522122
Päijänne	0.7291551

9.4.2 Temperature correlations in Port Charlotte and Bracadale

Table 9.4-2 shows computed correlations between maximum and minimum temperature for the Scottish catchments.

Table 9.4-2. Computed Pearson correlations of maximum and minimum temperature.

Catchment	Correlation *R* (max temp., min temp.)
Port Charlotte	0.9782175
Bracadale	0.9781269

Table 9.4-3 shows temperature data used for computing correlations for the Scottish catchments, and for other analyses in the study.

Table 9.4-3. Temperature data for the meteorological station Tiree, representing temperature in Port Charlotte and Bracadale.

Year	Month	Max temp.	Min. temp	Year	Month	Max temp.	Min. temp	Year	Month	Max temp.	Min. temp
2000	1	8,4	4,3	2005	9	15,8	11,1	2011	5	13,1	7,9
2000	2	8,4	3,6	2005	10	13,7*	9,7*	2011	6	14,3	8,8
2000	3	9,3	5,2	2005	11	10,3	5,6	2011	7	15,8	10,4
2000	4	9,6	4,6	2005	12	9,1	4,8	2011	8	15,7	10,4
2000	5	13,4	7,3	2006	1	8,5	4,8	2011	9	15,1	10,8
2000	6	14,1	9,3	2006	2	8,3	3,5	2011	10	12,9	9
2000	7	16,6	11,1	2006	3	7,9	2,6	2011	11	11,9	8
2000	8	17	11,5	2006	4	10,0*	4,9*	2011	12	8,5	3,5
2000	9	15,6	10,6	2006	5	12,8	7,2	2012	1	8,2	4,5
2000	10	12,4	8,1	2006	6	15,2	10,1	2012	2	8,8	5,5
2000	11	9,5	5,2	2006	7	17,7	12,6	2012	3	10,5	6,5
2000	12	8	4,5	2006	8	16,4	11,7	2012	4	10,2	4,1
2001	1	6,9	3,3	2006	9	16,4	12,1	2012	5	13,5	6,9
2001	2	7,1	3,1	2006	10	14,1	10,1	2012	6	14,5	8,9
2001	3	8	2,4	2006	11	10,7	6,3	2012	7	15,5	10,3
2001	4	9,9	4,3	2006	12	9,5	5,7	2012	8	17,1	11,7
2001	5	14	7,6	2007	1	9,4*	4,8*	2012	9	14,2	9,7
2001	6	13,7	8,8	2007	2	8,4	4,6	2012	10	11,6	5,7
2001	7	15,5	10,8	2007	3	9,3	4,3	2012	11	9,4	5,2
2001	8	16,6	11,3	2007	4	12,3	6,8	2012	12	8	3,5
2001	9	14,9	10	2007	5	12,8	7,2	2013	1	7,5	4,5
2001	10	14,1	10,4	2007	6	16,1	10,3	2013	2	6,9	2,9
2001	11	11	6,4	2007	7	16,2	11	2013	3	7	1,9
2001	12	8,6	4	2007	8	15,7	11	2013	4	9,5	3,4
2002	1	9,5	5,5	2007	9	14,7	9,8	2013	5	11,8	6,3

2002	2	8,6	3,9	2007	10	13,8	9,9	2013	6	15,1	9,1
2002	3	9,4	4,9	2007	11	10,9	6,9	2013	7	17,7	11,9
2002	4	10,8	6,2	2007	12	9,4	5,1	2013	8	16,5	11,6
2002	5	13,2	7,9	2008	1	8,5	3,4	2013	9	15,1	10,4
2002	6	14,5	10,3	2008	2	9	4,4	2013	10	13,2	8,8
2002	7	15,3	10,8	2008	3	8,5	3,6	2013	11	9,7	4,9
2002	8	16,8	11,7	2008	4	10,4	4,8	2013	12	9,5	5,3
2002	9	16	10,6	2008	5	15,3	8,9	2014	1	7,9	4,4
2002	10	11,6	7,1	2008	6	14,8	9,2	2014	2	7,9	3,8
2002	11	10,8	7,2	2008	7	17	11,4	2014	3	9,4	4,9
2002	12	8,2	4,5	2008	8	16,6	12,1	2014	4	12,1	6,8
2003	1	7,8	3,3	2008	9	15,1	10,2	2014	5	13,3	8,3
2003	2	7,7	4	2008	10	12	6,7	2014	6	15,7	11,1
2003	3	9,8	5,3	2008	11	9,7	5,7	2014	7	17,7	12,2
2003	4	12,2	6,4	2008	12	8	3,1	2014	8	16	11
2003	5	12,5	7,4	2009	1	7,9	3,4	2014	9	16,1	10,9
2003	6	15,4	10,6	2009	2	7,8	3,9	2014	10	13,3	8,1
2003	7	17,4	12,5	2009	3	9,3	4,3	2014	11	11,4	7,1
2003	8	17,7	12	2009	4	11,7	6,6	2014	12	8,7	3,8
2003	9	15,5	9,7	2009	5	13,3	7,3	2015	1	7,6	2,6
2003	10	11,9	7	2009	6	16,2	9,9	2015	2	7,6	2,8
2003	11	10,9	6,7	2009	7	16,8	11,6	2015	3	8,8	3,8
2003	12	8,8	4,3	2009	8	16,2	11,9	2015	4	10,4	4,5
2004	1	8,5	4,3	2009	9	15,1	10,9	2015	5	11,3	6,3
2004	2	8,1	3,1	2009	10	13,3	9,1	2015	6	13,2	8,7
2004	3	9,4	4,6	2009	11	10,2	5,9	2015	7	15,1	9,9
2004	4	11	6,6	2009	12	7,3	2,6	2015	8	15,9	10,9
2004	5	13,1	7,7	2010	1	6,3	1,4	2015	9	14,7	10,3
2004	6	14,9	10,2	2010	2	6,1	0,9	2015	10	13,5	8,6
2004	7	16,1	10,8	2010	3	8,7	3,3	2015	11	10,7	6,4
2004	8	18,1	12,5	2010	4	10,6	5,1	2015	12	9,8	5,1
2004	9	15,4	10,9	2010	5	12,3	6,8	2016	1	8	4
2004	10	12,6	5,7	2010	6	16	10,4	2016	2	7,4	2,5
2004	11	10,6	7,2	2010	7	16,1	11,4	2016	3	8,9	4,4
2004	12	9,7	5,1	2010	8	16	10,9	2016	4	9,5	4
2005	1	9,2	4,7	2010	9	15,2	11,3	2016	5	14,3	7,6
2005	2	7,7	3	2010	10	13,3	7,9	2016	6	16	10,8
2005	3	10	5,3	2010	11	8,4	3,2	2016	7	15,7	11
2005	4	11,2	5,6	2010	12	5,7	0,3	2016	8	16,7	12,1
2005	5	12,3	6,8	2011	1	7,8	3,2	2016	9	15,8	11,4
2005	6	15,3	10,6	2011	2	8,3	3,8	2016	10	13,4	9
2005	7	16,2	11,3	2011	3	9,1	5	2016	11	9,7	4,6
2005	8	16,4	11,8	2011	4	12,7	7,1	2016	12	10,4	6,1

9.4.3 Acid deposition correlations in all catchments

Table 9.4-4 shows computed correlations between sulphate and nitrate deposition. The data used for computing these is given in Table 9.4-5 (Jordalsvatnet), Table 9.4-6 (Glomma), Table 9.4-7 (Port Charlotte), Table 9.4-8 (Bracadale), Table 9.4-9 (Ätran) and Table 9.4-10 (Päijänne).

Table 9.4-4 Correlation between sulphate and nitrate deposition in the six catchments, over the period in focus.

Catchment	**Correlation *R* (sulphate, nitrate)**
Jordalsvatnet	0.9123388
Glomma	0.8532428
Port Charlotte	0.9646191
Bracadale	0.9513875
Ätran	0.9044957

Päijänne	0.9176667

Jordalsvatnet

Table 9.4-5. Observations for sulphate and nitrate deposition in Jordalsvatnet.

Year	Sulphate	Nitrate
2000	1130,074	1173,36
2001	955,2295	1003,513
2002	950,1389	1088,422
2003	1055,776	1183,19
2004	976,176	1093,324
2005	1019,336	1217,722
2006	825,1429	1139,156
2007	697,6135	980,4751
2008	622,2315	928,6978
2009	562,9093	908,4998
2010	468,2148	810,0932
2011	623,8369	1040,514
2012	478,4838	812,6992
2013	462,5908	806,3586
2014	739,5298	919,5156
2015	454,9999	839,2295

Glomma

Table 9.4-6. Observations for sulphate and nitrate deposition in Glomma.

Year	Sulphate	Nitrate
2000	177,6733	241,1716
2001	126,2601	178,3421
2002	119,2272	174,7013
2003	119,6611	183,0866
2004	119,7884	168,3846
2005	117,378	207,4253
2006	120,3278	207,7247
2007	70,95779	143,9458
2008	82,96169	168,0966
2009	78,20878	163,6831
2010	74,49058	142,9588
2011	71,50506	170,0049
2012	60,10648	142,8181
2013	45,41976	125,5932
2014	118,1819	160,3569

Port Charlotte

Table 9.4-7. Observations for sulphate and nitrate deposition in Port Charlotte.

Year	Sulphate	Nitrate
2000	424,2292	336,9183
2001	417,2787	324,3089
2002	420,3005	342,7253
2003	398,8842	356,5669
2004	297,8056	258,5927
2005	298,6729	281,2279
2006	307,0373	311,3492
2007	228,8542	223,8612
2008	229,6355	240,7682
2009	196,2703	212,2865
2010	190,4897	225,1128
2011	203,5499	219,2485
2012	176,6853	192,5395
2013	186,3754	211,5315
2014	206,6255	220,958
2015	186,9178	183,3638

Bracadale

Table 9.4-8. Observations for sulphate and nitrate deposition in Bracadale.

Year	Sulphate	Nitrate
2001	310,5795	273,4558
2002	307,8387	318,185
2003	334,3337	353,9791
2004	298,3954	268,5537
2005	272,8766	271,5987
2006	269,5965	311,958
2007	213,763	228,0186
2008	203,2707	225,8421
2009	185,1222	214,6802
2010	146,3056	159,6021
2011	197,2854	217,8308
2012	138,3821	165,1135
2013	163,0646	180,3559
2014	191,4627	198,8568
2015	185,1827	181,4485
2016	132,4995	165,3394

Ätran

Table 9.4-9. Observations for sulphate and nitrate deposition in Ätran.

Year	SO4	NO3
2000	593,1002	852,9535
2001	430,6806	641,761
2002	452,6789	626,1587
2003	399,2575	634,4637
2004	404,1522	625,9483
2005	358,9888	635,8241
2006	361,3361	693,5122
2007	291,3867	573,7128
2008	289,9476	611,8627
2009	258,801	536,4318
2010	234,7899	492,378
2011	262,8936	577,3841
2012	240,4659	564,875
2013	190,5968	461,1186

Päijänne

Table 9.4-10. Observations for sulphate and nitrate deposition in Päijänne.

Year	Sulphate	Nitrate
2001	200,2406	196,3815
2002	147,1607	170,1206
2003	214,0314	219,0271
2004	157,6872	199,5187
2005	182,7596	227,707
2006	151,7001	193,3646
2007	147,146	189,6541
2008	140,8569	186,7181
2009	106,6243	150,8118
2010	151,7702	193,6823
2011	116,6751	178,0543
2012	126,5426	177,0358
2013	82,17204	140,6419
2014	132,7358	168,7953
2015	95,98725	160,1627

9.5 Appendix E Data used in R scripts

9.5.1 Pre-processing of climate data for linear regression

To fit linear regression models of colour as a function of rainfall and of temperature, each colour value was linked to a rainfall and temperature value. Table 9.5-1 shows the method of linking the downloaded rainfall and temperature observations for the six catchments.

Table 9.5-1. Resolution used for linking the climate data on rainfall amount and temperature to measured colour values at the six sites.

Catchment	Rainfall	Temperature
Jordalsvatnet	monthly	mean temperature of the recent seven days
Glomma	monthly	mean temperature of the recent seven days
Port Charlotte	monthly	maximum temperature of that month
Bracadale	monthly	maximum temperature of that month
Ätran	precipitation of the last seven days	mean temperature the recent seven days
Päijänne	monthly	mean temperature of the month

9.5.2 DOM, rainfall and temperature

Here the pre-processed data for fitting the linear regression models of colour against temperature and rainfall are shown, for the six catchments. These are also the same observations for colour used in the Seasonal Kendall test. The tables given are Table 9.5-2 (Jordalsvatnet), Table 9.5-3 (Glomma), Table 9.5-4 (Port Charlotte), Table 9.5-5 (Bracadale), Table 9.5-6 (Ätran) and Table 9.5-7 (Päijänne).

Jordalsvatnet

Table 9.5-2. Date, colour, temperature and rainfall for Jordalsvatnet for all the available colour observations in Jordalsvatnet. Temperature and rainfall values were found by pre-processing downloaded daily and monthly observations, respectively.

Date	Colour	Temperature	Rainfall	Date	Colour	Temperature	Rainfall	Date	Colour	Temperature	Rainfall
2000-01-25	19	1,457142857	378,4	2007-09-10	18	11,54285714	363,1	2011-08-22	24	14,1	109,4
2000-02-08	12	4,785714286	330,2	2007-09-17	17	9,814285714	363,1	2011-08-29	22	15,52857143	109,4
2000-02-21	18	0,857142857	330,2	2007-09-24	16	10,28571429	363,1	2011-09-05	23	13,97142857	359,9
2000-04-25	13	9,242857143	115,5	2007-10-01	15	9,314285714	213,1	2011-09-12	22	12,75714286	359,9
2000-05-23	13	10,5	131,1	2007-10-08	17	9,457142857	213,1	2011-09-19	22	11,62857143	359,9
2000-06-27	12	13,51428571	176,8	2007-10-15	17	8,885714286	213,1	2011-09-26	19	11,95714286	359,9
2000-10-23	12	10,44285714	222,1	2007-10-22	15	7,9	213,1	2011-10-03	22	15,21428571	303
2000-11-27	23	8,085714286	154,6	2007-10-29	25	9,342857143	213,1	2011-10-10	23	8,942857143	303
2000-12-18	24	3,942857143	164,4	2007-11-05	25	6,114285714	373,8	2011-10-17	23	8,985714286	303
2001-01-22	24	-0,257142857	79	2007-11-12	26	3,6	373,8	2011-10-24	23	8,785714286	303
2001-03-19	23	2,142857143	111,9	2007-11-19	25	3,9	373,8	2011-10-31	26	11,55714286	303
2001-04-17	21	3,228571429	123,7	2007-11-26	27	2,928571429	373,8	2011-11-07	29	11,2	297,4
2001-05-29	20	10,21428571	77,8	2007-12-10	28	3,928571429	276,3	2011-11-14	29	6,571428571	297,4
2001-06-12	19	8,942857143	166,3	2007-12-17	25	3,485714286	276,3	2011-11-21	29	6,928571429	297,4
2001-07-30	19	15,68571429	148,2	2008-01-07	26	2,042857143	329	2011-11-28	31	7,714285714	297,4
2001-08-13	18	13,22857143	235	2008-01-14	27	4,157142857	329	2011-12-05	32	5,057142857	352,4

2001-08-27	19	16,08571429	235	2008-01-21	26	3,928571429	329	2011-12-12	27	2,171428571	352,4
2001-10-08	18	12,81428571	332,4	2008-01-28	23	4,371428571	329	2012-01-02	25	4,314285714	256,8
2001-11-19	25	4,914285714	367,3	2008-02-04	23	2,857142857	321,8	2012-01-09	24	3,014285714	256,8
2002-01-28	24	0,785714286	288,9	2008-02-11	25	5,385714286	321,8	2012-01-16	21	3,971428571	256,8
2002-03-04	23	1,371428571	188,3	2008-02-18	22	4,1	321,8	2012-01-23	23	2,285714286	256,8
2002-04-09	19	8,428571429	107,1	2008-02-25	22	5,485714286	321,8	2012-01-30	24	1,9	256,8
2002-05-21	19	12,8	102,5	2008-03-03	18	3,842857143	217	2012-02-06	31	-1,314285714	286,2
2002-06-03	17	14,21428571	203,4	2008-03-10	27	3,714285714	217	2012-02-13	22	1,485714286	286,2
2002-07-01	18	12,9	223,7	2008-03-25	20	0,457142857	217	2012-02-20	22	3,371428571	286,2
2002-08-05	18	22,51428571	165,8	2008-03-31	19	3,342857143	217	2012-02-27	22	4,942857143	286,2
2002-09-02	17	14,74285714	160,3	2008-04-07	19	6,014285714	120,8	2012-03-05	19	6,085714286	242,4
2002-09-30	19	11,77142857	160,3	2008-04-14	19	5,271428571	120,8	2012-03-12	17	5,628571429	242,4
2002-10-28	17	5,642857143	174,9	2008-04-21	18	7,142857143	120,8	2012-03-19	24	5,928571429	242,4
2002-11-25	24	1,142857143	118,5	2008-05-05	17	11,41428571	17,5	2012-03-26	23	7,628571429	242,4
2003-01-06	22	-3,014285714	368,8	2008-05-19	17	9,628571429	17,5	2012-04-16	20	5,628571429	101,7
2003-02-03	21	0,614285714	140	2008-05-26	20	11,18571429	17,5	2012-04-23	20	7,714285714	101,7
2003-04-22	18	12,12857143	82,9	2008-06-02	17	17,35714286	173	2012-05-07	20	6,557142857	117,5
2003-07-28	18	17,41428571	175,9	2008-06-09	18	18,24285714	173	2012-05-21	19	8,785714286	117,5
2003-09-15	19	14,41428571	364,5	2008-06-16	16	11,12857143	173	2012-06-04	18	9,414285714	54,8
2003-11-24	27	5,971428571	213,5	2008-07-07	17	19,34285714	114,4	2012-06-11	19	13,07142857	54,8
2004-01-26	24	1,928571429	182,1	2008-07-14	16	16	114,4	2012-06-18	19	11,94285714	54,8
2004-02-09	23	4,5	141,2	2008-07-21	16	14,32857143	114,4	2012-06-25	18	14,75714286	54,8
2004-02-23	23	2,685714286	141,2	2008-07-28	16	20,6	114,4	2012-07-02	19	14,2	182,7
2004-03-15	22	4,057142857	136,7	2008-08-04	16	19,77142857	166,4	2012-07-09	19	18,08571429	182,7
2004-03-29	22	4,842857143	136,7	2008-08-11	15	15,48571429	166,4	2012-07-16	18	13,51428571	182,7
2004-04-05	21	8,085714286	175,8	2008-09-15	16	14,31428571	145,3	2012-07-23	19	13,07142857	182,7
2004-04-19	21	9,457142857	175,8	2008-09-22	17	11,98571429	145,3	2012-07-30	18	14,87142857	182,7
2004-05-03	20	9,714285714	95,4	2008-09-29	17	11,01428571	145,3	2012-08-06	19	15,5	202,7
2004-05-10	20	14,51428571	95,4	2008-10-06	16	7,8	494,4	2012-08-13	19	14,77142857	202,7
2004-05-24	20	7,3	95,4	2008-10-13	17	11,3	494,4	2012-08-20	19	17,5	202,7
2004-06-01	19	12,81428571	120	2008-10-21	19	7,942857143	494,4	2012-08-27	18	13,78571429	202,7
2004-06-14	19	12,57142857	120	2008-10-27	20	7,614285714	494,4	2012-09-03	18	13,6	408,5
2004-06-28	20	14,44285714	120	2008-11-03	18	3,957142857	277,3	2012-09-10	18	12,32857143	408,5
2004-07-19	19	13,15714286	131,6	2008-11-10	22	6,9	277,3	2012-09-17	18	10,55714286	408,5
2004-08-02	19	17,54285714	155,1	2008-11-17	22	5,828571429	277,3	2012-09-24	20	8,2	408,5
2004-08-16	20	19,84285714	155,1	2008-11-24	1	0,728571429	277,3	2012-10-01	24	10,21428571	224,6
2004-08-30	17	13,84285714	155,1	2008-12-01	18	3,9	168,2	2012-10-08	20	8,671428571	224,6
2004-09-13	19	13,37142857	381	2008-12-08	22	1,514285714	168,2	2012-10-15	18	6,9	224,6
2004-09-27	19	10,32857143	381	2008-12-15	21	2,4	168,2	2012-10-22	21	9,114285714	224,6
2004-10-11	19	8,985714286	151	2009-01-05	22	-0,457142857	197,7	2012-10-29	22	3,614285714	224,6
2004-10-26	19	9,328571429	151	2009-01-12	21	4,828571429	197,7	2012-11-05	28	5,2	393,1
2004-11-08	19	6,414285714	354,6	2009-01-19	20	4,357142857	197,7	2012-11-12	31	5,742857143	393,1
2004-11-13	24	6,142857143	354,6	2009-01-26	20	4,485714286	197,7	2012-11-19	32	7,585714286	393,1
2004-11-22	25	0,471428571	354,6	2009-02-02	20	2	176,9	2012-11-26	32	7,242857143	393,1
2004-11-23	25	0,385714286	354,6	2009-02-09	24	-1,442857143	176,9	2012-12-03	34	-0,528571429	161,6
2004-11-24	25	0,728571429	354,6	2009-02-16	19	-1,014285714	176,9	2012-12-10	33	-4,014285714	161,6
2004-12-06	25	6,728571429	567,6	2009-02-23	20	3,471428571	176,9	2012-12-17	31	2	161,6
2004-12-15	26	7,057142857	567,6	2009-03-02	20	3,485714286	235,7	2013-01-02	30	3,885714286	150,4
2004-12-20	25	3,185714286	567,6	2009-03-09	21	5,214285714	235,7	2013-01-07	30	5,971428571	150,4
2005-01-03	23	3,557142857	465,6	2009-03-16	19	5,242857143	235,7	2013-01-14	33	-1,214285714	150,4
2005-01-14	21	5,257142857	465,6	2009-03-23	20	4,7	235,7	2013-01-21	32	-4,971428571	150,4
2005-01-17	20	5,628571429	465,6	2009-03-30	6,6	3,628571429	235,7	2013-01-28	32	-0,471428571	150,4
2005-01-31	19	2,085714286	465,6	2009-04-14	19	9,871428571	93,4	2013-02-04	32	2,471428571	79,3
2005-02-14	17	2,828571429	175,6	2009-04-20	19	9,257142857	93,4	2013-02-11	33	-1,471428571	79,3
2005-02-28	17	-0,457142857	175,6	2009-04-27	19	10,55714286	93,4	2013-02-18	30	1,3	79,3
2005-03-14	17	2,085714286	169,2	2009-05-04	18	10,65714286	176	2013-02-25	30	0,814285714	79,3
2005-03-29	16	7,585714286	169,2	2009-05-11	19	8,128571429	176	2013-03-04	30	2,942857143	17,9
2005-04-11	16	4,742857143	149,8	2009-05-25	20	11,08571429	176	2013-03-11	30	0,714285714	17,9
2005-04-25	16	7,628571429	149,8	2009-06-02	20	12,88571429	45,1	2013-03-18	29	1,714285714	17,9
2005-05-09	15	7,485714286	162,7	2009-06-08	19	11,07142857	45,1	2013-04-08	27	2,657142857	219,5
2005-05-23	15	9,285714286	162,7	2009-06-15	18	11,57142857	45,1	2013-04-15	29	5,385714286	219,5
2005-06-13	16	10,45714286	139,3	2009-06-22	20	11,94285714	45,1	2013-04-22	24	7,071428571	219,5
2005-06-20	15	13,8	139,3	2009-06-29	18	20,04285714	45,1	2013-05-06	22	5,9	129,7
2005-07-04	15	16,08571429	88,9	2009-07-06	19	20,64285714	146,9	2013-05-13	23	9,285714286	129,7
2005-07-18	15	15,31428571	88,9	2009-07-13	19	16,57142857	146,9	2013-05-21	24	14,67142857	129,7
2005-08-08	15	14,1	224,8	2009-07-20	19	16,65714286	146,9	2013-05-27	23	10,97142857	129,7
2005-08-22	14	15,44285714	224,8	2009-07-27	19	14,82857143	146,9	2013-06-03	22	14,88571429	158,9
2005-09-05	12	14,75714286	450,3	2009-08-03	20	15,9	200	2013-06-10	23	12,5	158,9
2005-09-16	35	10,77142857	450,3	2009-08-10	17	17,88571429	200	2013-06-17	23	13,6	158,9
2005-09-19	15	10,88571429	450,3	2009-08-17	18	13,9	200	2013-06-24	23	14,21428571	158,9
2005-10-03	15	10,78571429	255,7	2009-08-24	19	16,28571429	200	2013-07-01	22	13,71428571	167,6
2005-10-10	14	12,95714286	255,7	2009-08-31	17	14,17142857	200	2013-07-08	23	14,32857143	167,6
2005-10-24	17	6,342857143	255,7	2009-09-07	16	14,12857143	360,8	2013-07-15	24	13,32857143	167,6
2005-11-07	25	11,2	558,8	2009-09-14	17	13,08571429	360,8	2013-07-22	24	15,7	167,6
2005-11-21	28	2,742857143	558,8	2009-09-21	18,5	12,25714286	360,8	2013-07-29	24	19,35714286	167,6
2005-11-28	28	4,014285714	558,8	2009-09-28	19	11,57142857	360,8	2013-08-05	23	17,05714286	214,7
2005-12-05	28	3,2	211,1	2009-10-06	18	6,342857143	123,2	2013-08-12	26	14,24285714	214,7

2005-12-19	26,3	2,728571429	211,1	2009-10-12	18	6,571428571	123,2	2013-08-19	22	14,21428571	214,7
2006-01-02	26	-1,771428571	156,6	2009-10-19	18	6,942857143	123,2	2013-08-26	23	16,15714286	214,7
2006-01-09	26	1,057142857	156,6	2009-10-26	18	7,985714286	123,2	2013-09-02	23	13,5	202,1
2006-01-16	25	6,214285714	156,6	2009-11-02	18	8,057142857	266,3	2013-09-09	25	15,82857143	202,1
2006-01-23	26	2,228571429	156,6	2009-11-09	30	7,057142857	266,3	2013-09-16	22	13,25714286	202,1
2006-01-30	24	1,871428571	156,6	2009-11-16	30	5,871428571	266,3	2013-09-23	23	11,12857143	202,1
2006-02-06	27	3,8	132,9	2009-11-23	29	8,885714286	266,3	2013-09-30	23	9,842857143	202,1
2006-02-13	25	3	132,9	2009-11-30	28	5,485714286	266,3	2013-10-07	23	11,62857143	343,1
2006-02-20	23	3,457142857	132,9	2009-12-07	30	6,071428571	70,5	2013-10-14	21	9,542857143	343,1
2006-02-27	23	2,385714286	132,9	2009-12-14	29	4,8	70,5	2013-10-21	25	7,414285714	343,1
2006-03-06	25	-2,214285714	54,9	2010-01-04	30	-5,385714286	37	2013-10-28	24	10,57142857	343,1
2006-03-13	24	-0,371428571	54,9	2010-01-11	28	-8,942857143	37	2013-11-04	22	7,728571429	352,7
2006-03-20	22	1,542857143	54,9	2010-01-18	30	-1,371428571	37	2013-11-11	30	5,442857143	352,7
2006-03-27	22	1,142857143	54,9	2010-01-25	28	-0,942857143	37	2013-11-18	38	7,114285714	352,7
2006-04-03	22	4,671428571	205,4	2010-02-01	29	-1,385714286	39	2013-11-25	35	2,742857143	352,7
2006-04-18	22	5,242857143	205,4	2010-02-08	29	-1,228571429	39	2013-12-02	35	5,514285714	433,6
2006-04-25	20	6,942857143	205,4	2010-02-15	27	-0,957142857	39	2013-12-09	33	2,657142857	433,6
2006-05-02	20	9,528571429	70,4	2010-02-22	32	-2,271428571	39	2013-12-16	32	7,514285714	433,6
2006-05-08	20	16,65714286	70,4	2010-03-01	29	-1,1	204,3	2013-12-23	31	5,857142857	433,6
2006-05-15	21	9,742857143	70,4	2010-03-08	29	0,271428571	204,3	2013-12-30	29	6,471428571	433,6
2006-05-22	22	9,942857143	70,4	2010-03-15	29	2,7	204,3	2014-01-06	28	7,4	101,2
2006-05-29	21	8,742857143	70,4	2010-03-22	28	4,928571429	204,3	2014-01-13	27	3,342857143	101,2
2006-06-06	19	10,11428571	130,5	2010-04-06	26	6,528571429	176,1	2014-01-20	27	2,528571429	101,2
2006-06-12	20	15,01428571	130,5	2010-04-12	27	7,671428571	176,1	2014-01-27	27	1,828571429	101,2
2006-06-19	20	14,15714286	130,5	2010-04-19	24	5,771428571	176,1	2014-02-03	26	3,5	200,2
2006-06-26	21	12,75714286	130,5	2010-04-26	26	6,085714286	176,1	2014-02-10	27	5,957142857	200,2
2006-07-03	19	16,54285714	180,5	2010-05-03	25	7,1	56	2014-02-17	25	4,9	200,2
2006-07-10	18	17,62857143	180,5	2010-05-31	24	10,22857143	56	2014-02-24	26	4,214285714	200,2
2006-07-17	21	14,15714286	180,5	2010-06-07	25	11,98571429	75	2014-03-03	25	6,928571429	278,4
2006-07-24	20	18,24285714	180,5	2010-06-14	23	12,8	75	2014-03-10	24	6,885714286	278,4
2006-07-31	19	19,61428571	180,5	2010-06-21	24	11,62857143	75	2014-03-17	25	4,557142857	278,4
2006-08-07	19	18,9	94,5	2010-06-28	22	13,51428571	75	2014-03-24	23	5,157142857	278,4
2006-08-14	20	17,81428571	94,5	2010-07-05	23	15,4	171,6	2014-03-31	24	7,442857143	278,4
2006-08-21	19	17,14285714	94,5	2010-07-12	19	15,14285714	171,6	2014-04-07	23	7,314285714	131,1
2006-08-28	19	17,07142857	94,5	2010-07-19	23	15,94285714	171,6	2014-04-22	23	9,457142857	131,1
2006-09-04	18	14,91428571	226,9	2010-07-26	24	15,14285714	171,6	2014-04-28	22	13,24285714	131,1
2006-09-11	21	13,62857143	226,9	2010-08-02	22	15,28571429	167,7	2014-05-05	23	7,242857143	96,7
2006-09-18	18	17,9	226,9	2010-08-09	25	15,4	167,7	2014-05-13	23	10,55714286	96,7
2006-10-02	18	13,8	288,3	2010-08-16	22	17,35714286	167,7	2014-05-19	23	11,52857143	96,7
2006-10-09	18	11,98571429	288,3	2010-08-23	23	17,3	167,7	2014-05-26	21	13,38571429	96,7
2006-10-16	18	11,57142857	288,3	2010-08-30	23	12,25714286	167,7	2014-06-02	22	14,07142857	58,6
2006-10-23	18	10,61428571	288,3	2010-09-06	22	13,14285714	241	2014-06-10	22	16,35714286	58,6
2006-10-30	19	7,514285714	288,3	2010-09-13	22	15,42857143	241	2014-06-16	22	14,88571429	58,6
2006-11-06	17	6,642857143	475,3	2010-09-20	21	10,08571429	241	2014-06-23	22	12,68571429	58,6
2006-11-13	23	5,357142857	475,3	2010-09-27	24	10,78571429	241	2014-06-30	22	14,54285714	58,6
2006-11-20	24	7	475,3	2010-10-04	21	11,22857143	284,5	2014-07-07	23	15,21428571	162,7
2006-11-27	26	8,657142857	475,3	2010-10-12	21	10,3	284,5	2014-07-14	23	20,81428571	162,7
2006-12-04	20	9,257142857	496,7	2010-10-18	22	6,842857143	284,5	2014-07-21	23	18,77142857	162,7
2006-12-11	24	6,642857143	496,7	2010-10-25	22	3,485714286	284,5	2014-07-28	22	22,15714286	162,7
2006-12-18	24	5,357142857	496,7	2010-11-01	24	8,485714286	95,6	2014-08-04	21	17,62857143	206
2006-12-27	23	6,942857143	496,7	2010-11-08	31	4,828571429	95,6	2014-08-11	23	17,68571429	206
2007-01-02	22	5,571428571	423,9	2010-11-15	31	2,785714286	95,6	2014-08-18	22	14,21428571	206
2007-01-08	22	5,7	423,9	2010-11-22	33	1,471428571	95,6	2014-08-25	22	13,05714286	206
2007-01-15	20	5,014285714	423,9	2010-11-29	32	-4,257142857	95,6	2014-09-01	23	15,44285714	127,9
2007-01-22	18	2	423,9	2010-12-06	32	-5,685714286	76,3	2014-09-08	22	15,15714286	127,9
2007-01-29	18	0,242857143	423,9	2010-12-13	31	0,242857143	76,3	2014-09-15	22	14,28571429	127,9
2007-02-05	18	4,942857143	134,5	2011-01-03	32	-0,557142857	236,4	2014-09-22	22	13,07142857	127,9
2007-02-19	19	4,471428571	134,5	2011-01-10	33	2,4	236,4	2014-09-29	23	11,4	127,9
2007-02-26	18	2,457142857	134,5	2011-01-17	33	2,914285714	236,4	2014-10-06	23	14,01428571	473,1
2007-03-05	18	5,257142857	263,4	2011-01-24	30	3,128571429	236,4	2014-10-13	23	10,72857143	473,1
2007-03-12	16	6,771428571	263,4	2011-01-31	32	1,428571429	236,4	2014-10-20	22	8,671428571	473,1
2007-03-19	18	5,157142857	263,4	2011-02-14	28	0,985714286	169,4	2014-10-27	23	10,61428571	473,1
2007-03-26	17	5,642857143	263,4	2011-02-21	29	-1,571428571	169,4	2014-11-03	23	9,8	169,3
2007-04-10	17	4,285714286	181,1	2011-02-28	29	2,028571429	169,4	2014-11-10	22	8,885714286	169,3
2007-04-16	16	9,985714286	181,1	2011-03-07	23	2,342857143	219,1	2014-11-17	21	8,4	169,3
2007-04-23	16	6,142857143	181,1	2011-03-14	26	2	219,1	2014-11-24	22	5,571428571	169,3
2007-05-07	15	9,514285714	188	2011-03-21	27	4,728571429	219,1	2014-12-01	28	4,114285714	423,4
2007-05-14	16	7,671428571	188	2011-03-28	25	3,3	219,1	2014-12-08	32	4,842857143	423,4
2007-05-29	16	11,02857143	188	2011-04-04	25	6,085714286	148	2014-12-15	30	3,671428571	423,4
2007-06-04	14	15,85714286	24,2	2011-04-11	23	7,828571429	148	2014-12-22	29	3,985714286	423,4
2007-06-11	18	20,2	24,2	2011-05-02	23	10,85714286	136,4	2014-12-29	30	-0,242857143	423,4
2007-06-18	13	13,04285714	24,2	2011-05-09	23	12,68571429	136,4	2015-01-05	28,4	4,685714286	516,1
2007-06-25	13	16	24,2	2011-05-23	23	9,928571429	136,4	2015-01-12	28	4,928571429	516,1
2007-07-02	16	15,04285714	245,9	2011-06-06	16	11,61428571	248,1	2015-01-19	25	3,342857143	516,1
2007-07-09	17	16,87142857	245,9	2011-06-20	23	12,9	248,1	2015-01-26	26	1,8	516,1
2007-07-16	16	13,27142857	245,9	2011-06-27	23	13,34285714	248,1	2015-02-02	25	1,614285714	246,4
2007-07-23	17	15,2	245,9	2011-07-04	23	14,58571429	103	2015-02-09	25	1,314285714	246,4

2007-07-30	17	14,1	245,9	2011-07-11	22	16	103	2015-02-16	22	4,828571429	246,4
2007-08-06	18	14,87142857	330,8	2011-07-18	23	15,98571429	103	2015-02-23	22	4,314285714	246,4
2007-08-13	17	15,37142857	330,8	2011-07-25	23	16,14285714	103	2015-03-02	22	4,857142857	349
2007-08-20	17	13,24285714	330,8	2011-08-01	22	15,35714286	109,4	2015-03-09	21	4,885714286	349
2007-08-27	17	14,1	330,8	2011-08-08	22	16,57142857	109,4				
2007-09-03	19	10,32857143	363,1	2011-08-15	24	14,74285714	109,4				

Glomma

Table 9.5-3. Date, colour, temperature and rainfall for Jordalsvatnet for all the available colour observations in Jordalsvatnet. Temperature and rainfall values were found by pre-processing downloaded daily and monthly observations, respectively.

Date	Colour	Temperature	Rainfall	Date	Colour	Temperature	Rainfall	Date	Colour	Temperature	Rainfall
2000-01-04	22	-5,625	13	2003-06-03	25	13,17142857	36,9	2007-01-09	29	-2,1	61,9
2000-01-11	28	-0,057142857	13	2003-06-10	18	15,5	36,9	2007-01-16	44	-2,228571429	61,9
2000-01-18	26	-2,385714286	13	2003-06-17	21	12,47142857	36,9	2007-01-23	28	-7,557142857	61,9
2000-01-25	19	-5,442857143	13	2003-06-24	22	13,25714286	36,9	2007-01-30	25	-9,714285714	61,9
2000-02-01	21	-6,028571429	11,6	2003-07-01	38	15,61428571	79	2007-02-13	23	-14,22857143	13,1
2000-02-08	20	-2,628571429	11,6	2003-07-15	25	17,17142857	79	2007-02-20	25	-3,285714286	13,1
2000-02-15	21	-1,185714286	11,6	2003-07-22	17	20,05714286	79	2007-02-27	23	-7,228571429	13,1
2000-02-22	22	-9,357142857	11,6	2003-07-29	16	16,57142857	79	2008-01-02	31	-1,985714286	71,7
2000-02-29	21	-2,2	11,6	2003-08-05	18	16,6	105,3	2008-01-07	30	-4	71,7
2000-03-07	22	-0,714285714	19,2	2003-08-12	15	17,92857143	105,3	2008-01-21	55	-1,228571429	71,7
2000-03-14	24	-2,785714286	19,2	2003-08-19	16	13,85714286	105,3	2008-02-04	32	-5,128571429	20,3
2000-03-21	20	1,185714286	19,2	2003-08-26	18	13,18571429	105,3	2008-02-18	29	-4,4	20,3
2000-03-28	19	-1,085714286	19,2	2003-09-02	18	9,471428571	19,3	2008-03-03	36	-0,542857143	29,7
2000-04-04	19	-0,114285714	42,4	2003-09-09	16	11,9	19,3	2008-03-31	34	-1,614285714	29,7
2000-04-11	5	1,542857143	42,4	2003-09-16	14	12,7	19,3	2008-04-14	52	2,214285714	26,1
2000-04-17	31	2,7	42,4	2003-09-23	14	9,114285714	19,3	2008-04-29	60	8,428571429	26,1
2000-04-25	63	7,3	42,4	2003-09-30	66	6,628571429	19,3	2008-05-13	41	11,78571429	59,6
2000-05-02	59	8,228571429	35,3	2003-10-07	39	5	10,5	2008-05-26	26	7,785714286	59,6
2000-05-09	40	11,07142857	35,3	2003-10-14	27	3,728571429	10,5	2008-06-09	21	18,57142857	46,4
2000-05-15	27	13,27142857	35,3	2003-10-21	23	-0,571428571	10,5	2008-06-23	18	12,64285714	46,4
2000-05-23	17	11,1	35,3	2003-10-28	19	-1,157142857	10,5	2008-07-07	17	16,92857143	31,1
2000-05-29	19	9,085714286	35,3	2003-11-04	25	0,9	22,3	2008-07-21	20	14,12857143	31,1
2000-06-06	30	9,585714286	53,4	2003-11-11	32	0,942857143	22,3	2008-08-04	15	16,98571429	100,4
2000-06-13	23	12,81428571	53,4	2003-11-18	36	-0,071428571	22,3	2008-08-18	30	12,98571429	100,4
2000-06-20	15	11,77142857	53,4	2003-11-25	23	-4,057142857	22,3	2008-09-01	29	12,68571429	21,6
2000-06-27	12	12,45714286	53,4	2003-12-02	29	0,471428571	33,5	2008-09-15	39	8,814285714	21,6
2000-07-04	25	14,7	106,8	2003-12-09	34	-1,685714286	33,5	2008-09-29	23	9,1	21,6
2000-07-11	22	11,88571429	106,8	2003-12-16	32	-2,371428571	33,5	2008-10-13	87	7,6	52,9
2000-07-18	23	14,47142857	106,8	2004-01-06	23	-11,01428571	19,8	2008-10-27	35	6,371428571	52,9
2000-07-25	23	16,6	106,8	2004-01-13	22	-4,342857143	19,8	2008-11-10	38	0,485714286	40,6
2000-08-01	22	15,35714286	64,4	2004-01-20	19	-10,54285714	19,8	2008-11-24	36	-2,071428571	40,6
2000-08-08	18	13,74285714	64,4	2004-01-27	20	-8,785714286	19,8	2008-12-08	26	-5,885714286	18
2000-08-15	19	14,57142857	64,4	2004-02-03	19	-7,957142857	13,6	2009-01-05	25	-12,22857143	39,6
2000-08-22	25	11,7	64,4	2004-02-10	22	-2,942857143	13,6	2009-01-19	27	-4,785714286	39,6
2000-08-29	35	12,21428571	64,4	2004-02-17	19	-2,585714286	13,6	2009-02-02	25	-12,41428571	28,5
2000-09-05	20	10,37142857	15,7	2004-03-02	21	-5,285714286	13,7	2009-02-16	22	-11,34285714	28,5
2000-09-12	18	10,11428571	15,7	2004-03-09	20	-5,428571429	13,7	2009-03-02	22	-3,828571429	14,2
2000-09-19	29	8,714285714	15,7	2004-03-16	22	-0,228571429	13,7	2009-03-16	23	-0,414285714	14,2
2000-09-26	22	8,385714286	15,7	2004-03-23	41	2,528571429	13,7	2009-03-30	21	-3,4	14,2
2000-10-03	18	10,84285714	115,6	2004-03-30	37	0,7	13,7	2009-04-14	50	4,342857143	17,4
2000-10-10	28	8,9	115,6	2004-04-13	48	3,371428571	21	2009-04-27	67	7,957142857	17,4
2000-10-17	61	8,857142857	115,6	2004-04-20	53	7,4	21	2009-05-11	37	7,571428571	28,7
2000-10-24	33	7,028571429	115,6	2004-04-27	67	7,114285714	21	2009-05-25	22	11,47142857	28,7
2000-10-31	41	2,414285714	115,6	2004-05-04	46	8,557142857	26,5	2009-06-08	20	9,428571429	32,6
2000-11-07	55	4,214285714	110,4	2004-05-11	28	13,18571429	26,5	2009-06-22	20	12,44285714	32,6
2000-11-14	60	3,842857143	110,4	2004-05-25	17	7,485714286	26,5	2009-07-06	13	20,34285714	114,9
2000-11-21	57	1,171428571	110,4	2004-06-01	16	12,12857143	67,3	2009-08-03	30	14,4	87,8
2000-11-28	55	2,028571429	110,4	2004-06-08	14	13,74285714	67,3	2009-08-17	44	12,31428571	87,8
2000-12-05	46	2,885714286	22,9	2004-06-15	12	13,55714286	67,3	2009-08-31	28	13,05714286	87,8
2000-12-12	53	2,957142857	22,9	2004-06-22	13	10,22857143	67,3	2009-09-14	41	11,68571429	20,8
2000-12-19	62	-0,757142857	22,9	2004-06-29	18	12,82857143	67,3	2009-09-28	27	11,7	20,8
2001-01-02	30	-10,37142857	25,6	2004-07-06	23	13,04285714	51,2	2009-10-12	32	1,314285714	30,8
2001-01-09	29	-1,771428571	25,6	2004-07-13	20	14,34285714	51,2	2009-10-26	32	2,6	30,8
2001-01-16	25	-7,9	25,6	2004-07-20	16	13,28571429	51,2	2009-11-09	41	0,742857143	56,6
2001-01-23	24	-9,971428571	25,6	2004-07-27	13	14,64285714	51,2	2009-11-23	72	1,257142857	56,6
2001-01-30	25	-2,128571429	25,6	2004-08-03	13	17,48571429	96,3	2009-12-07	42	-4,585714286	38,8
2001-02-06	25	-18,9	8,7	2004-08-10	13	18,9	96,3	2010-01-04	24	-14,31428571	8,7
2001-02-14	23	-6,942857143	8,7	2004-08-17	18	16,18571429	96,3	2010-01-18	9	-10,58571429	8,7
2001-02-20	23	-1,985714286	8,7	2004-08-24	14	12,82857143	96,3	2010-02-01	19	-11,42857143	6,8
2001-02-27	23	-9,928571429	8,7	2004-08-31	20	11,72857143	96,3	2010-02-16	23	-8,942857143	6,8

2001-03-06	23	-12,64285714	6,4	2004-09-07	53	12,57142857	58,7	2010-03-01	13	-10,84285714	25,9
2001-03-13	23	-0,014285714	6,4	2004-09-14	23	9,971428571	58,7	2010-03-16	12	-2	25,9
2001-03-20	23	-5,6	6,4	2004-09-21	35	9,228571429	58,7	2010-04-07	44	2,057142857	19,6
2001-03-27	20	-6,185714286	6,4	2004-09-28	52	9,185714286	58,7	2010-04-20	75	3,214285714	19,6
2001-04-03	23	-0,128571429	41,5	2004-10-05	26	7,271428571	36,1	2010-05-04	52	5,042857143	22
2001-04-10	39	2,4	41,5	2004-10-12	43	4,914285714	36,1	2010-05-19	54	10,68571429	22
2001-04-17	38	-0,371428571	41,5	2004-10-19	28	4,242857143	36,1	2010-06-01	30	11,58571429	81
2001-04-24	33	2,8	41,5	2004-10-26	39	3,457142857	36,1	2010-06-14	29	12,31428571	81
2001-04-30	54	4,457142857	41,5	2004-11-02	48	-0,1	47,9	2010-06-30	25	14,68571429	81
2001-05-08	63	7,971428571	18	2004-11-09	41	1,457142857	47,9	2010-07-12	23	16,95714286	89,6
2001-05-14	49	12,94285714	18	2004-11-16	28	2,014285714	47,9	2010-08-10	31	16,11428571	101
2001-05-22	34	8,114285714	18	2004-11-23	24	-6,514285714	47,9	2010-08-25	30	14,08571429	101
2001-05-29	31	9,714285714	18	2004-11-30	24	-5,414285714	47,9	2010-09-15	26	11,58571429	42,9
2001-06-05	24	10,1	60	2004-12-07	28	-3,385714286	8	2010-09-21	56	8,171428571	42,9
2001-06-12	26	9,628571429	60	2004-12-14	25	-3,514285714	8	2010-10-06	45	6,957142857	50,9
2001-06-18	24	11,32857143	60	2005-01-04	32	-3,185714286	40,1	2010-10-20	36	2,971428571	50,9
2001-06-26	22	15,97142857	60	2005-01-11	31	-0,328571429	40,1	2010-11-03	34	4,028571429	3,7
2001-07-03	15	17,02857143	92,9	2005-01-18	34	1,114285714	40,1	2010-11-17	33	-5,171428571	3,7
2001-07-10	17	20,11428571	92,9	2005-01-25	37	-4,128571429	40,1	2010-12-01	24	-14,15714286	21,4
2001-07-17	14	12,77142857	92,9	2005-02-01	34	-1,6	1,9	2010-12-15	23	-8,257142857	21,4
2001-07-24	28	14,54285714	92,9	2005-02-08	28	-0,271428571	1,9	2011-01-05	23	-7,514285714	28,1
2001-07-31	26	16,04285714	92,9	2005-02-15	25	-3,714285714	1,9	2011-01-19	21	-9,828571429	28,1
2001-08-07	17	12,28571429	89,9	2005-02-22	22	-5,114285714	1,9	2011-02-02	14	-7,671428571	9,7
2001-08-14	33	12,71428571	89,9	2005-03-01	22	-7,585714286	11,7	2011-02-16	14	-11,5	9,7
2001-08-21	24	15,12857143	89,9	2005-03-08	24	-5,742857143	11,7	2011-03-02	22	-5,942857143	11,5
2001-08-28	19	13,6	89,9	2005-03-15	23	-5,171428571	11,7	2011-03-16	22	-4,314285714	11,5
2001-09-04	25	11,25714286	25	2005-03-29	23	3,328571429	11,7	2011-03-30	23	-1,285714286	11,5
2001-09-11	29	10,45714286	25	2005-04-05	20	4,171428571	10,4	2011-04-13	44	6,071428571	19,1
2001-09-18	47	10,84285714	25	2005-04-12	37	4,428571429	10,4	2011-05-04	26	7,871428571	47,2
2001-09-25	42	10,05714286	25	2005-04-19	46	4,242857143	10,4	2011-05-18	27	8,114285714	47,2
2001-10-02	27	6,042857143	68,2	2005-04-26	39	5,871428571	10,4	2011-06-07	30	14,77142857	167,9
2001-10-09	60	9,471428571	68,2	2005-05-03	42	6,757142857	24,3	2011-06-27	33	14,12857143	167,9
2001-10-16	62	6,4	68,2	2005-05-10	42	5,957142857	24,3	2011-07-13	29	15,17142857	124,5
2001-10-23	33	2,757142857	68,2	2005-05-24	33	7,8	24,3	2011-08-10	33	15,31428571	112,5
2001-10-30	30	5,314285714	68,2	2005-05-31	40	9,985714286	24,3	2011-08-23	41	12,81428571	112,5
2001-11-06	49	1,814285714	13,4	2005-06-07	27	9,271428571	27,7	2011-09-20	42	9,485714286	76,8
2001-11-13	28	-0,728571429	13,4	2005-06-14	21	11,24285714	27,7	2011-10-05	34	11,85714286	22,1
2001-11-20	24	-0,4	13,4	2005-06-21	21	14,82857143	27,7	2011-10-19	40	2,6	22,1
2001-11-27	24	-1,871428571	13,4	2005-06-28	19	14,58571429	27,7	2011-11-01	35	5,6	14
2001-12-04	24	-0,271428571	29,1	2005-07-05	15	17,25714286	31,3	2011-11-15	35	0,614285714	14
2001-12-11	27	-4,5	29,1	2005-07-12	13	21,14285714	31,3	2011-11-29	28	2,871428571	14
2001-12-18	23	-2,2	29,1	2005-07-19	11	16,68571429	31,3	2011-12-13	30	-5,357142857	31,2
2002-01-08	20	-10,72857143	33,1	2005-07-26	13	15,17142857	31,3	2012-01-10	31	-7,285714286	41,9
2002-01-15	20	-7,071428571	33,1	2005-08-02	17	15,48571429	89,5	2012-01-25	25	-10,58571429	41,9
2002-01-22	23	-2,9	33,1	2005-08-09	16	13,21428571	89,5	2012-01-31	19	-8,8	41,9
2002-01-29	22	-9,214285714	33,1	2005-08-16	35	15,1	89,5	2012-02-07	22	-13,12857143	10,6
2002-02-05	35	-2,228571429	32,6	2005-08-23	20	15,87142857	89,5	2012-02-21	20	-2,885714286	10,6
2002-02-12	35	-3,471428571	32,6	2005-08-30	22	12,67142857	89,5	2012-03-06	20	-1,085714286	4,7
2002-02-19	37	-2,685714286	32,6	2005-09-06	20	12,92857143	28,6	2012-03-19	29	2,628571429	4,7
2002-02-26	21	-5,628571429	32,6	2005-09-13	18	10,67142857	28,6	2012-04-17	22	2,6	53,2
2002-03-05	19	-3	8,8	2005-09-20	19	10,6	28,6	2012-05-02	52	7,728571429	32,9
2002-03-12	25	-0,871428571	8,8	2005-09-27	20	10,7	28,6	2012-05-30	24	15,11428571	32,9
2002-03-19	25	-2,371428571	8,8	2005-10-04	23	8,542857143	48,8	2012-06-13	17	12,5	68,8
2002-03-26	29	0,657142857	8,8	2005-10-11	37	8,728571429	48,8	2012-06-26	19	14,12857143	68,8
2002-04-02	33	2,314285714	9,6	2005-10-18	34	5,157142857	48,8	2012-07-03	16	14	70,2
2002-04-09	40	3,642857143	9,6	2005-10-25	30	-0,385714286	48,8	2012-07-17	45	13,28571429	70,2
2002-04-15	55	3,971428571	9,6	2005-11-01	45	5,471428571	40,1	2012-07-30	46	15,7	70,2
2002-04-23	52	6,842857143	9,6	2005-11-08	64	7,242857143	40,1	2012-08-14	39	14,74285714	96,1
2002-04-29	54	6,914285714	9,6	2005-11-15	52	5,5	40,1	2012-09-03	42	12,85714286	16,8
2002-05-07	48	8,371428571	86,1	2005-11-22	35	-0,428571429	40,1	2012-09-18	23	9,728571429	16,8
2002-05-14	26	11,67142857	86,1	2005-11-29	29	-3,2	40,1	2012-10-02	56	7,928571429	56,1
2002-05-21	23	11,2	86,1	2005-12-06	27	-3,785714286	13,3	2012-10-16	36	2,357142857	56,1
2002-05-28	17	11,61428571	86,1	2005-12-13	24	-2,228571429	13,3	2012-10-30	39	-1,914285714	56,1
2002-06-04	31	13,37142857	51,8	2005-12-20	19	-5,157142857	13,3	2012-11-13	59	-0,114285714	50,5
2002-06-11	18	16,97142857	51,8	2006-01-03	19	-8,342857143	34,5	2012-11-27	59	2	50,5
2002-06-19	22	14,21428571	51,8	2006-01-10	19	-9,885714286	34,5	2012-12-11	34	-12,95714286	22,4
2002-06-25	17	13,45714286	51,8	2006-01-17	23	0,457142857	34,5	2013-01-08	35	-3,214285714	20,3
2002-07-02	21	12,37142857	92,6	2006-01-24	21	-8,1	34,5	2013-01-22	18	-15,67142857	20,3
2002-07-09	21	13,1	92,6	2006-01-31	21	-2,842857143	34,5	2013-02-05	23	-6,5	12,8
2002-07-16	49	16,31428571	92,6	2006-02-07	22	-5,142857143	33	2013-02-19	17	-5,428571429	12,8
2002-07-23	30	16,51428571	92,6	2006-02-14	22	-7,657142857	33	2013-03-05	16	-0,828571429	1,3
2002-07-30	40	16,97142857	92,6	2006-02-21	20	-5,514285714	33	2013-03-19	12	-7,528571429	1,3
2002-08-06	24	19,15714286	21,8	2006-02-28	20	-1,771428571	33	2013-04-16	33	1,914285714	10,5
2002-08-13	20	17,48571429	21,8	2006-03-07	23	-9,657142857	8,3	2013-05-28	44	12,68571429	135
2002-08-20	20	18,47142857	21,8	2006-03-14	24	-9,1	8,3	2013-06-11	26	12,12857143	133,2
2002-08-27	19	17,61428571	21,8	2006-03-21	20	-2,657142857	8,3	2013-06-25	21	15,37142857	133,2
2002-09-03	14	14,08571429	23,8	2006-03-28	21	-4,314285714	8,3	2013-07-02	34	13,91428571	20,7

2002-09-10	20	14,5	23,8	2006-04-04	26	0,257142857	12,1	2013-07-16	22	15,62857143	20,7
2002-09-17	19	12,45714286	23,8	2006-04-18	46	2,857142857	12,1	2013-07-30	20	19,05714286	20,7
2002-09-24	18	6,914285714	23,8	2006-04-25	51	4,542857143	12,1	2013-08-13	15	14,34285714	86,1
2002-10-01	17	6,242857143	47,3	2006-05-02	72	4,7	46,9	2013-09-03	18	12,57142857	32,2
2002-10-08	18	4,4	47,3	2006-05-09	69	12,02857143	46,9	2013-09-17	18	11,47142857	32,2
2002-10-15	15	1,528571429	47,3	2006-05-23	38	8,157142857	46,9	2013-10-01	25	5,757142857	45,5
2002-10-22	15	-2,471428571	47,3	2006-05-30	37	9,357142857	46,9	2013-10-15	18	5,857142857	45,5
2002-10-29	31	0,442857143	47,3	2006-06-06	28	10,94285714	13,4	2013-10-29	37	5,171428571	45,5
2002-11-05	27	-6,057142857	25,2	2006-06-13	20	18,65714286	13,4	2013-11-12	41	0,485714286	17,3
2002-11-12	28	-5,4	25,2	2006-06-20	15	16,68571429	13,4	2013-11-26	16	-6,228571429	17,3
2002-11-19	22	-4,457142857	25,2	2006-06-27	14	13,28571429	13,4	2013-12-10	21	-5,442857143	48,3
2002-11-26	18	-4,014285714	25,2	2006-07-04	19	18,78571429	30,7	2014-01-07	57	1,828571429	43,8
2002-12-03	18	-5,042857143	7,7	2006-07-11	15	18,17142857	30,7	2014-01-21	31	-8,785714286	43,8
2002-12-10	19	-8,128571429	7,7	2006-07-18	14	16,51428571	30,7	2014-02-04	24	-3,857142857	32
2002-12-17	21	-14,6	7,7	2006-07-25	13	19,97142857	30,7	2014-02-18	35	-0,314285714	32
2003-01-02	23	-11,98571429	33,1	2006-07-31	12	18,88571429	30,7	2014-03-04	40	0,728571429	14,3
2003-01-07	23	-16,88571429	33,1	2006-08-08	11	18,37142857	95	2014-03-19	37	0,557142857	14,3
2003-01-14	22	-7,128571429	33,1	2006-08-15	14	15,88571429	95	2014-04-01	35	4,157142857	13
2003-01-21	25	0,885714286	33,1	2006-08-22	25	15,55714286	95	2014-04-23	50	7,5	13
2003-01-28	34	-3,171428571	33,1	2006-08-29	22	14,62857143	95	2014-05-06	38	3,928571429	22,1
2003-02-04	28	-8,485714286	6,7	2006-09-05	29	13,15714286	37,9	2014-05-20	33	11,7	22,1
2003-02-11	23	-5,442857143	6,7	2006-09-12	46	11,71428571	37,9	2014-06-03	27	15,47142857	34,6
2003-02-18	21	-7,714285714	6,7	2006-09-19	23	12,75714286	37,9	2014-06-17	22	15,05714286	34,6
2003-02-25	22	-8,514285714	6,7	2006-09-26	19	13,85714286	37,9	2014-07-01	17	11,62857143	60,7
2003-03-04	19	-6,6	2,7	2006-10-03	18	11,32857143	93,9	2014-07-15	18	19,77142857	60,7
2003-03-11	23	-0,014285714	2,7	2006-10-10	43	9,228571429	93,9	2014-07-30	14	20	60,7
2003-03-18	28	1,385714286	2,7	2006-10-17	48	6,285714286	93,9	2014-08-12	17	16,35714286	92,9
2003-03-25	28	1,328571429	2,7	2006-10-24	34	4,928571429	93,9	2014-08-26	20	12,1	92,9
2003-04-02	34	2,828571429	12,4	2006-10-31	65	0,371428571	93,9	2014-09-09	18	13,58571429	9,9
2003-04-09	39	0,885714286	12,4	2006-11-07	41	-1,185714286	47	2014-09-23	18	8,685714286	9,9
2003-04-14	34	2,071428571	12,4	2006-11-14	33	-2,085714286	47	2014-10-07	14	9,342857143	78,6
2003-04-22	43	7,771428571	12,4	2006-11-21	64	1,214285714	47	2014-10-21	53	4,6	78,6
2003-04-29	71	3,8	12,4	2006-11-28	55	3,371428571	47	2014-11-04	40	3,457142857	52,3
2003-05-06	61	4,614285714	69,8	2006-12-05	50	4,057142857	33,3	2014-11-18	40	2,085714286	52,3
2003-05-13	59	7,242857143	69,8	2006-12-12	60	2,628571429	33,3	2014-12-02	46	-1,642857143	15
2003-05-20	45	8,085714286	69,8	2006-12-19	55	-2,214285714	33,3	2014-12-16	33	-1,242857143	15
2003-05-27	37	9,742857143	69,8	2007-01-02	27	-2,957142857	61,9				

Port Charlotte

Table 9.5-4. Date, colour, temperature and rainfall for Port Charlotte, for all the dates where colour observations in Port Charlotte were available. Duplicates appear when there are colour observations from the same month in the same year. Empty fields appear when observations of temperature or rainfall are lacking.

Date	Colour	Temperature	Rainfall	Date	Colour	Temperature	Rainfall
2000-01-24 08:00:00 UTC	51	8,4	124,8	2008-12-23 08:30:00 UTC	59	8	123,6
2000-05-02 09:10:00 UTC	49	13,4	43,4	2009-01-06 09:00:00 UTC	55	7,9	151,8
2000-08-22 08:30:00 UTC	72	17	87,6	2009-02-03 09:00:00 UTC	57	7,8	47,6
2000-08-29 10:30:00 UTC	70	17	87,6	2009-03-03 08:30:00 UTC	52	9,3	88,3
2000-09-19 08:30:00 UTC	110	15,6	137,2	2009-03-24 08:00:00 UTC	64	9,3	88,3
2000-10-24 09:00:00 UTC	122	12,4	226,4	2009-03-31 06:50:00 UTC	64	9,3	88,3
2000-11-21 09:30:00 UTC	75	9,5	128	2009-04-28 09:20:00 UTC	77	11,7	111,4
2000-12-12 10:00:00 UTC	115	8	165,6	2009-05-26 09:30:00 UTC	107	13,3	94
2001-01-23 09:30:00 UTC	90	6,9	109,6	2009-06-16 09:00:00 UTC	107	16,2	46,8
2001-04-24 12:00:00 UTC	67	9,9	31,6	2009-06-23 09:30:00 UTC	111	16,2	46,8
2001-08-21 14:00:00 UTC	223	16,6	95,6	2009-07-21 08:30:00 UTC	124	16,8	101,2
2001-08-28 00:00:00 UTC	259	16,6	95,6	2009-08-18 07:55:00 UTC	222	16,2	206,4
2001-08-28 10:00:00 UTC	256	16,6	95,6	2009-09-08 10:55:00 UTC	230	15,1	72,4
2001-09-18 06:10:00 UTC	206	14,9	88,2	2009-09-15 09:15:00 UTC	275	15,1	72,4
2001-10-23 09:30:00 UTC	185	14,1	183,8	2009-10-13 09:00:00 UTC	38	13,3	164,2
2001-11-08 07:40:00 UTC	200	11	145,2	2009-11-10 11:45:00 UTC	152	10,2	239,8
2001-11-09 07:35:00 UTC	172	11	145,2	2009-12-03 09:30:00 UTC	126	7,3	97,6
2001-11-10 07:35:00 UTC	184	11	145,2	2009-12-08 12:50:00 UTC	79	7,3	97,6
2001-11-11 09:30:00 UTC	230	11	145,2	2010-01-05 08:00:00 UTC	88	6,3	72,8
2001-11-12 08:30:00 UTC	186	11	145,2	2010-02-02 09:40:00 UTC	68	6,1	74,2
2001-11-13 07:35:00 UTC	148	11	145,2	2010-03-02 08:30:00 UTC	74	8,7	53,9
2001-11-14 07:35:00 UTC	173	11	145,2	2010-03-23 10:00:00 UTC	68	8,7	53,9
2001-11-15 07:30:00 UTC	156	11	145,2	2010-03-30 08:30:00 UTC	83	8,7	53,9
2001-11-16 07:35:00 UTC	153	11	145,2	2010-04-27 09:20:00 UTC	100	10,6	57
2001-11-17 08:45:00 UTC	168	11	145,2	2010-05-25 08:05:00 UTC	99	12,3	51,8
2001-11-18 09:15:00 UTC	155	11	145,2	2010-06-15 09:00:00 UTC	99	16	30,4
2001-11-19 07:30:00 UTC	158	11	145,2	2010-07-20 09:45:00 UTC	112	16,1	129
2001-11-20 07:30:00 UTC	155	11	145,2	2010-08-17 09:00:00 UTC	130	16	98,6
2001-11-21 07:30:00 UTC	166	11	145,2	2010-09-07 10:10:00 UTC	134	15,2	108,2

2001-11-22 07:35:00 UTC	145	11	145,2	2010-09-14 09:00:00 UTC	138	15,2	108,2
2001-11-23 07:30:00 UTC	146	11	145,2	2010-10-12 07:30:00 UTC	163	13,3	123,6
2001-11-24 00:00:00 UTC	142	11	145,2	2010-11-09 08:27:00 UTC	126	8,4	140,4
2001-11-25 00:00:00 UTC	141	11	145,2	2010-11-29 10:40:00 UTC	108	8,4	140,4
2001-11-26 07:20:00 UTC	141	11	145,2	2010-12-07 08:40:00 UTC	79	5,7	49
2001-11-27 00:00:00 UTC	143	11	145,2	2011-01-06 13:00:00 UTC	59	7,8	100
2001-11-28 00:00:00 UTC	158	11	145,2	2011-02-01 09:00:00 UTC	87	8,3	124
2001-11-29 07:35:00 UTC	140	11	145,2	2011-03-01 08:00:00 UTC	80	9,1	63,8
2001-11-30 07:35:00 UTC	133	11	145,2	2011-03-22 11:25:00 UTC	74	9,1	63,8
2001-12-01 09:15:00 UTC	121	8,6	89,6	2011-03-29 09:15:00 UTC	70	9,1	63,8
2001-12-02 15:15:00 UTC	134	8,6	89,6	2011-04-26 07:35:00 UTC	86	12,7	80,2
2001-12-03 08:15:00 UTC	136	8,6	89,6	2011-05-24 10:10:00 UTC	112	13,1	158,2
2001-12-04 07:30:00 UTC	103	8,6	89,6	2011-06-14 10:15:00 UTC	82	14,3	84,4
2001-12-04 12:30:00 UTC	4	8,6	89,6	2011-06-21 08:00:00 UTC	95	14,3	84,4
2001-12-05 07:30:00 UTC	132	8,6	89,6	2011-07-19 09:45:00 UTC	88	15,8	50,8
2001-12-06 07:30:00 UTC	24	8,6	89,6	2011-08-16 09:00:00 UTC	112	15,7	123,2
2001-12-08 10:15:00 UTC	120	8,6	89,6	2011-09-06 10:00:00 UTC	142	15,1	165
2001-12-09 09:30:00 UTC	135	8,6	89,6	2011-09-13 10:00:00 UTC	183	15,1	165
2001-12-10 07:30:00 UTC	140	8,6	89,6	2011-10-11 09:00:00 UTC	196	12,9	176,4
2001-12-11 07:30:00 UTC	150	8,6	89,6	2011-11-08 10:30:00 UTC	193	11,9	121,6
2001-12-12 07:35:00 UTC	131	8,6	89,6	2011-11-29 08:10:00 UTC	169	11,9	121,6
2001-12-17 00:00:00 UTC	120	8,6	89,6	2011-12-06 09:40:00 UTC	152	8,5	262,2
2002-06-18 10:00:00 UTC	172	14,5	135,8	2012-01-05 09:10:00 UTC	35	8,2	137,8
2002-09-03 10:00:00 UTC	164	16	80	2012-01-31 10:20:00 UTC	30	8,2	137,8
2002-11-05 09:30:00 UTC	148	10,8	136,8	2012-02-28 08:30:00 UTC	46	8,8	133,2
2002-11-26 12:20:00 UTC	120	10,8	136,8	2012-03-20 07:30:00 UTC	61	10,5	43,4
2002-12-05 12:00:00 UTC	1,5	8,2	52	2012-03-27 09:10:00 UTC	59	10,5	43,4
2002-12-12 10:30:00 UTC	30	8,2	52	2012-04-24 09:30:00 UTC	61	10,2	51,4
2002-12-19 00:00:00 UTC	100	8,2	52	2012-05-22 09:10:00 UTC	57	13,5	56,6
2002-12-19 12:00:00 UTC	100	8,2	52	2012-06-12 08:00:00 UTC	61	14,5	82,2
2003-01-07 10:00:00 UTC	108	7,8	100,8	2012-06-19 09:15:00 UTC	69	14,5	82,2
2003-02-04 12:10:00 UTC	65	7,7	55,6	2012-07-17 08:15:00 UTC	106	15,5	82,8
2003-03-04 11:00:00 UTC	55	9,8	78	2012-08-14 09:00:00 UTC	160	17,1	62,8
2003-04-08 10:00:00 UTC	48	12,2	52	2012-09-04 09:30:00 UTC	180	14,2	98
2003-04-15 09:30:00 UTC	47	12,2	52	2012-09-11 10:15:00 UTC	198	14,2	98
2003-06-10 08:10:00 UTC	76	15,4	69	2012-09-12 12:18:00 UTC	216	14,2	98
2003-06-17 10:00:00 UTC	107	15,4	69	2012-10-04 07:20:00 UTC	201	11,6	102,8
2003-06-24 10:00:00 UTC	101	15,4	69	2012-10-09 08:45:00 UTC	181	11,6	102,8
2003-07-01 08:30:00 UTC	100	17,4	75	2012-11-06 07:17:00 UTC	159	9,4	163
2003-07-08 08:30:00 UTC	124	17,4	75	2012-11-27 08:10:00 UTC	145	9,4	163
2003-07-15 20:44:00 UTC	118	17,4	75	2012-12-04 08:30:00 UTC	138	8	177,8
2003-07-22 09:00:00 UTC	130	17,4	75	2013-01-08 07:25:00 UTC	123	7,5	140,4
2003-07-29 11:00:00 UTC	107	17,4	75	2013-01-29 09:00:00 UTC	116	7,5	140,4
2003-08-26 00:01:00 UTC	3	17,7	33,6	2013-02-05 07:00:00 UTC	92	6,9	72
2003-08-26 21:14:00 UTC	120	17,7	33,6	2013-02-27 08:17:00 UTC	59	6,9	72
2003-09-09 10:00:00 UTC	111	15,5	92,2	2013-03-05 09:30:00 UTC	57	7	25
2003-10-07 10:00:00 UTC	96	11,9	58	2013-03-27 12:59:00 UTC	49	7	25
2003-11-04 10:45:00 UTC	77	10,9	183,6	2013-04-02 09:00:00 UTC	47	9,5	97,4
2003-11-11 10:40:00 UTC	74	10,9	183,6	2013-04-23 06:30:00 UTC	43	9,5	97,4
2004-03-23 10:00:00 UTC	60	9,4	86,2	2013-04-30 09:15:00 UTC	51	9,5	97,4
2004-04-13 09:50:00 UTC	56	11	79,6	2013-05-21 08:30:00 UTC	73	11,8	92,4
2004-05-11 10:50:00 UTC	83	13,1	34,6	2013-05-28 07:50:00 UTC	75	11,8	92,4
2004-06-01 10:00:00 UTC	85	14,9	68,2	2013-06-18 09:00:00 UTC	96	15,1	58,6
2004-06-08 09:40:00 UTC	92	14,9	68,2	2013-06-25 09:15:00 UTC	90	15,1	58,6
2004-07-06 12:00:00 UTC	35	16,1	75,2	2013-07-16 10:00:00 UTC	98	17,7	48
2004-08-03 09:30:00 UTC	153	18,1	122,2	2013-07-23 08:40:00 UTC	104	17,7	48
2004-08-31 08:00:00 UTC	178	18,1	122,2	2013-08-13 12:00:00 UTC	104	16,5	102,6
2004-09-28 11:20:00 UTC	158	15,4	192,8	2013-08-20 08:00:00 UTC	110	16,5	102,6
2004-10-26 11:00:00 UTC	127	12,6	143,3	2013-09-10 08:10:00 UTC	58	15,1	109,7
2004-11-23 11:15:00 UTC	66	10,6	93,6	2013-09-17 09:15:00 UTC	123	15,1	109,7
2005-01-06 09:00:00 UTC	69	9,2	148,3	2013-10-08 10:15:00 UTC	123	13,2	118
2005-02-01 08:00:00 UTC	39	7,7	71	2013-11-05 08:30:00 UTC	145	9,7	126,8
2005-04-12 08:40:00 UTC	40	11,2	109,2	2013-11-12 09:30:00 UTC	127	9,7	126,8
2005-05-10 09:10:00 UTC	58	12,3	86	2013-12-03 09:45:00 UTC	106	9,5	219,4
2005-06-07 08:50:00 UTC	134	15,3	85,8	2013-12-10 07:30:00 UTC	79	9,5	219,4
2005-07-05 09:45:00 UTC	151	16,2	39,2	2014-01-21 07:15:00 UTC	47	7,9	187,4
2005-08-02 09:30:00 UTC	151	16,4	119	2014-01-21 08:00:00 UTC	46	7,9	187,4
2005-08-09 11:30:00 UTC	148	16,4	119	2014-02-04 07:00:00 UTC	58	7,9	206
2005-09-27 08:00:00 UTC	157	15,8	140	2014-02-04 07:20:00 UTC	58	7,9	206
2005-10-11 09:00:00 UTC	142		126	2014-03-04 07:00:00 UTC	70	9,4	100,6
2005-11-08 09:30:00 UTC	153	10,3	109,8	2014-03-04 07:10:00 UTC	70	9,4	100,6
2005-12-06 20:20:00 UTC	72	9,1	111,4	2014-04-01 07:30:00 UTC	79	12,1	48
2006-01-10 20:41:00 UTC	66	8,5	76,6	2014-04-15 08:30:00 UTC	80	12,1	48
2006-02-07 20:33:00 UTC	69	8,3	59	2014-04-29 08:10:00 UTC	75	12,1	48
2006-03-07 10:00:00 UTC	65	7,9	114,4	2014-05-20 09:00:00 UTC	140	13,3	110
2006-03-21 12:30:00 UTC	67	7,9	114,4	2014-05-27 07:00:00 UTC	121	13,3	110
2006-04-04 08:20:00 UTC	77		81,2	2014-05-27 07:40:00 UTC	118	13,3	110

2006-05-02 10:30:00 UTC	71	12,8	98,8	2014-06-03 09:00:00 UTC	119	15,7	47,4
2006-06-27 09:30:00 UTC	42	15,2	69	2014-06-24 07:30:00 UTC	125	15,7	47,4
2006-07-25 08:10:00 UTC	126	17,7	82,2	2014-07-15 10:15:00 UTC	113	17,7	118,2
2006-08-22 08:20:00 UTC	116	16,4	65,6	2014-07-22 07:30:00 UTC	155	17,7	118,2
2006-09-19 09:15:00 UTC	205	16,4	123,2	2014-07-22 08:15:00 UTC	147	17,7	118,2
2006-10-17 08:40:00 UTC	262	14,1	184,6	2014-08-12 07:45:00 UTC	163	16	100,6
2006-11-14 09:45:00 UTC	21	10,7	136,4	2014-08-26 07:55:00 UTC	168	16	100,6
2006-12-12 10:20:00 UTC	55	9,5	178	2014-09-16 08:30:00 UTC	163	16,1	27
2007-01-09 10:10:00 UTC	46			2014-09-23 20:56:00 UTC	161	16,1	27
2007-02-06 08:00:00 UTC	26	8,4	106	2014-10-21 07:00:00 UTC	132	13,3	250,4
2007-03-06 09:45:00 UTC	52	9,3	76,6	2014-10-21 07:17:00 UTC	127	13,3	250,4
2007-04-03 11:05:00 UTC	40	12,3	46,8	2014-10-28 08:45:00 UTC	107	13,3	250,4
2007-04-10 09:00:00 UTC	41	12,3	46,8	2014-11-04 20:34:00 UTC	122	11,4	128,4
2007-05-01 10:00:00 UTC	48	12,8	69,8	2014-11-18 08:30:00 UTC	172	11,4	128,4
2007-05-29 10:15:00 UTC	57	12,8	69,8	2014-12-09 07:10:00 UTC	153	8,7	186,8
2007-06-26 09:30:00 UTC	72	16,1	63,6	2014-12-30 07:10:00 UTC	61	8,7	186,8
2007-07-24 12:00:00 UTC	76	16,2	57,4	2015-01-20 07:00:00 UTC	38	7,6	177,6
2007-08-21 08:30:00 UTC	148	15,7	114	2015-01-20 07:15:00 UTC	38	7,6	177,6
2007-09-18 09:30:00 UTC	132	14,7	66,4	2015-02-03 08:45:00 UTC	32	7,6	96,4
2007-10-16 09:00:00 UTC	123	13,8	117,6	2015-02-17 07:00:00 UTC	31	7,6	96,4
2007-11-13 09:30:00 UTC	170	10,9	98	2015-03-17 09:00:00 UTC	37	8,8	140,6
2007-12-11 09:30:00 UTC	84	9,4	100,4	2015-03-24 07:15:00 UTC	38	8,8	140,6
2008-01-08 09:30:00 UTC	76	8,5	161,7	2015-04-21 07:40:00 UTC	41	10,4	60,6
2008-02-05 08:00:00 UTC	60	9	109,9	2015-04-21 08:15:00 UTC	41	10,4	60,6
2008-03-04 08:30:00 UTC	31	8,5	126,2	2015-05-05 12:15:00 UTC	42	11,3	123,4
2008-04-01 08:30:00 UTC	23	10,4	64,4	2015-05-11 13:30:00 UTC	55	11,3	123,4
2008-04-29 08:25:00 UTC	25	10,4	64,4	2015-06-09 07:30:00 UTC	80	13,2	68,8
2008-05-27 09:30:00 UTC	29	15,3	33,8	2015-06-09 11:00:00 UTC	83	13,2	68,8
2008-06-24 08:00:00 UTC	38	14,8	109,4	2015-07-28 07:00:00 UTC	154	15,1	165,8
2008-07-08 11:00:00 UTC	40	17	82,8	2015-07-28 08:00:00 UTC	157	15,1	165,8
2008-07-22 09:15:00 UTC	37	17	82,8	2015-08-04 08:00:00 UTC	157	15,9	74,7
2008-08-19 10:00:00 UTC	118	16,6	107,6	2015-08-18 09:00:00 UTC	92	15,9	74,7
2008-09-16 11:10:00 UTC	135	15,1	79,4	2015-09-01 08:30:00 UTC	237	14,7	40,9
2008-09-30 09:15:00 UTC	147	15,1	79,4	2015-09-15 08:30:00 UTC	175	14,7	40,9
2008-10-14 08:00:00 UTC	140	12	179,6	2015-09-22 09:30:00 UTC	212	14,7	40,9
2008-11-11 09:10:00 UTC	74	9,7	117,2	2015-10-06 08:30:00 UTC	215	13,5	73,8
2008-12-09 07:00:00 UTC	56	8	123,6	2015-10-13 08:00:00 UTC	201	13,5	73,8

Bracadale

Table 9.5-5. Date, colour, temperature and rainfall for Bracadale, for all the dates where colour observations in Bracadale were available. Duplicates appear when there are colour observations from the same month in the same year. Empty fields appear when observations of temperature or rainfall are lacking.

Date	Colour	Temperature	Rainfall	Date	Colour	Temperature	Rainfall
2001-01-10 09:00:00 UTC	78	6,9	109,6	2007-06-25 09:55:00 UTC	45	16,1	63,6
2001-01-11 09:10:00 UTC	74	6,9	109,6	2007-07-25 09:35:00 UTC	63	16,2	57,4
2001-01-18 09:20:00 UTC	38	6,9	109,6	2007-08-23 09:00:00 UTC	86	15,7	114
2001-01-24 09:45:00 UTC	76	6,9	109,6	2007-09-19 09:15:00 UTC	145	14,7	66,4
2001-01-24 09:55:00 UTC	75	6,9	109,6	2007-10-16 10:40:00 UTC	158	13,8	117,6
2001-01-31 09:10:00 UTC	64	6,9	109,6	2007-11-12 09:45:00 UTC	70	10,9	98
2001-02-06 09:00:00 UTC	71	7,1	60,5	2007-12-14 09:20:00 UTC	57	9,4	100,4
2001-02-07 11:05:00 UTC	63	7,1	60,5	2008-01-08 09:10:00 UTC	52	8,5	161,7
2001-02-14 11:05:00 UTC	97	7,1	60,5	2008-02-05 11:25:00 UTC	24	9	109,9
2001-02-20 11:50:00 UTC	77	7,1	60,5	2008-03-05 10:10:00 UTC	22	8,5	126,2
2001-02-22 10:05:00 UTC	79	7,1	60,5	2008-03-31 11:00:00 UTC	32	8,5	126,2
2001-03-02 10:05:00 UTC	50	8	30,2	2008-04-29 09:10:00 UTC	44	10,4	64,4
2001-03-08 09:50:00 UTC	48	8	30,2	2008-05-29 11:00:00 UTC	32	15,3	33,8
2001-03-08 11:30:00 UTC	46	8	30,2	2008-06-26 09:50:00 UTC	71	14,8	109,4
2001-03-14 08:50:00 UTC	57	8	30,2	2008-07-22 10:50:00 UTC	105	17	82,8
2001-03-20 09:50:00 UTC	41	8	30,2	2008-08-19 09:50:00 UTC	77	16,6	107,6
2001-03-21 09:40:00 UTC	43	8	30,2	2008-09-16 09:00:00 UTC	197	15,1	79,4
2001-03-28 11:25:00 UTC	31	8	30,2	2008-09-24 09:30:00 UTC	145	15,1	79,4
2001-04-04 09:20:00 UTC	74	9,9	31,6	2008-10-01 09:30:00 UTC	191	12	179,6
2001-04-04 09:45:00 UTC	72	9,9	31,6	2008-10-08 09:30:00 UTC	127	12	179,6
2001-04-11 10:35:00 UTC	63	9,9	31,6	2008-10-15 09:45:00 UTC	132	12	179,6
2001-04-18 08:50:00 UTC	72	9,9	31,6	2008-10-17 09:20:00 UTC	125	12	179,6
2001-04-18 09:00:00 UTC	70	9,9	31,6	2008-10-22 10:35:00 UTC	109	12	179,6
2001-04-18 09:10:00 UTC	68	9,9	31,6	2008-10-28 08:50:00 UTC	37	12	179,6
2001-04-24 11:00:00 UTC	61	9,9	31,6	2008-11-04 08:40:00 UTC	45	9,7	117,2
2001-04-26 11:25:00 UTC	51	9,9	31,6	2008-11-13 08:40:00 UTC	38	9,7	117,2
2001-04-30 11:10:00 UTC	84	9,9	31,6	2008-11-14 10:30:00 UTC	49	9,7	117,2
2001-04-30 11:15:00 UTC	78	9,9	31,6	2008-11-21 10:00:00 UTC	57	9,7	117,2
2001-05-02 08:50:00 UTC	61	14	22,6	2008-11-26 09:20:00 UTC	46	9,7	117,2

2001-05-10 09:55:00 UTC	54	14	22,6	2008-12-03 09:10:00 UTC	43	8	123,6
2001-05-10 10:05:00 UTC	53	14	22,6	2008-12-11 09:50:00 UTC	45	8	123,6
2001-05-15 08:20:00 UTC	43	14	22,6	2008-12-11 10:00:00 UTC	43	8	123,6
2001-05-15 08:35:00 UTC	42	14	22,6	2009-01-06 10:10:00 UTC	29	7,9	151,8
2001-05-17 12:00:00 UTC	64	14	22,6	2009-02-04 09:40:00 UTC	25	7,8	47,6
2001-05-23 10:00:00 UTC	51	14	22,6	2009-03-02 09:15:00 UTC	73	9,3	88,3
2001-05-24 09:55:00 UTC	42	14	22,6	2009-03-30 09:40:00 UTC	56	9,3	88,3
2001-05-29 09:45:00 UTC	50	14	22,6	2009-05-01 10:10:00 UTC	85	13,3	94
2001-05-29 09:55:00 UTC	49	14	22,6	2009-05-28 10:15:00 UTC	99	13,3	94
2001-06-11 11:00:00 UTC	97	13,7	61,8	2009-06-24 09:15:00 UTC	92	16,2	46,8
2001-06-13 09:55:00 UTC	88	13,7	61,8	2009-07-02 11:00:00 UTC	52	16,8	101,2
2001-06-25 10:30:00 UTC	78	13,7	61,8	2009-07-09 09:55:00 UTC	61	16,8	101,2
2001-06-27 09:30:00 UTC	68	13,7	61,8	2009-07-21 09:50:00 UTC	114	16,8	101,2
2001-07-10 09:20:00 UTC	91	15,5	63	2009-08-17 08:55:00 UTC	171	16,2	206,4
2001-09-20 11:15:00 UTC	94	14,9	88,2	2009-09-17 09:00:00 UTC	111	15,1	72,4
2001-09-26 09:30:00 UTC	66	14,9	88,2	2009-10-16 08:55:00 UTC	83	13,3	164,2
2001-10-02 10:15:00 UTC	108	14,1	183,8	2009-11-11 09:25:00 UTC	125	10,2	239,8
2001-10-03 09:15:00 UTC	88	14,1	183,8	2009-12-08 09:35:00 UTC	51	7,3	97,6
2001-10-10 09:10:00 UTC	109	14,1	183,8	2010-01-12 09:15:00 UTC	31	6,3	72,8
2001-10-16 09:45:00 UTC	126	14,1	183,8	2010-02-04 08:45:00 UTC	62	6,1	74,2
2001-10-17 09:10:00 UTC	128	14,1	183,8	2010-03-05 08:30:00 UTC	51	8,7	53,9
2001-10-24 10:00:00 UTC	110	14,1	183,8	2010-03-31 09:55:00 UTC	72	8,7	53,9
2001-10-24 10:40:00 UTC	107	14,1	183,8	2010-04-26 10:00:00 UTC	71	10,6	57
2001-10-29 10:30:00 UTC	92	14,1	183,8	2010-05-24 09:15:00 UTC	104	12,3	51,8
2001-11-01 11:40:00 UTC	109	11	145,2	2010-06-25 10:10:00 UTC	37	16	30,4
2001-11-07 09:40:00 UTC	92	11	145,2	2010-07-22 08:55:00 UTC	146	16,1	129
2001-11-12 17:45:00 UTC	82	11	145,2	2010-08-18 09:20:00 UTC	216	16	98,6
2001-11-14 08:40:00 UTC	76	11	145,2	2010-09-14 09:15:00 UTC	139	15,2	108,2
2001-11-21 09:20:00 UTC	123	11	145,2	2010-10-11 08:40:00 UTC	72	13,3	123,6
2001-11-27 10:10:00 UTC	75	11	145,2	2010-11-08 10:45:00 UTC	61	8,4	140,4
2001-11-29 10:10:00 UTC	42	11	145,2	2010-12-15 10:10:00 UTC	56	5,7	49
2001-12-05 10:40:00 UTC	62	8,6	89,6	2011-01-06 11:05:00 UTC	85	7,8	100
2001-12-12 09:30:00 UTC	52	8,6	89,6	2011-01-28 11:10:00 UTC	67	7,8	100
2001-12-18 09:50:00 UTC	46	8,6	89,6	2011-02-28 10:30:00 UTC	41	8,3	124
2002-01-10 10:00:00 UTC	41	9,5	155	2011-03-28 10:35:00 UTC	32	9,1	63,8
2002-01-31 11:15:00 UTC	17	9,5	155	2011-04-26 10:05:00 UTC	58	12,7	80,2
2002-02-06 10:40:00 UTC	18	8,6	187,2	2011-05-25 09:20:00 UTC	60	13,1	158,2
2002-02-14 09:25:00 UTC	30	8,6	187,2	2011-06-21 10:40:00 UTC	61	14,3	84,4
2002-02-14 09:45:00 UTC	30	8,6	187,2	2011-07-18 10:50:00 UTC	158	15,8	50,8
2002-02-21 10:30:00 UTC	36	8,6	187,2	2011-08-16 10:25:00 UTC	141	15,7	123,2
2002-02-28 10:20:00 UTC	23	8,6	187,2	2011-09-15 10:05:00 UTC	154	15,1	165
2002-03-07 10:05:00 UTC	33	9,4	82	2011-10-10 10:20:00 UTC	113	12,9	176,4
2002-03-13 09:30:00 UTC	13	9,4	82	2011-11-08 09:25:00 UTC	87	11,9	121,6
2002-03-13 09:30:00 UTC	13	9,4	82	2011-12-09 10:30:00 UTC	22	8,5	262,2
2002-03-21 08:25:00 UTC	14	9,4	82	2012-01-06 09:55:00 UTC	25	8,2	137,8
2002-03-28 09:05:00 UTC	19	9,4	82	2012-02-01 10:40:00 UTC	27	8,8	133,2
2002-04-10 10:10:00 UTC	22	10,8	100,4	2012-02-29 09:30:00 UTC	98	8,8	133,2
2002-04-25 09:10:00 UTC	46	10,8	100,4	2012-03-27 10:30:00 UTC	50	10,5	43,4
2002-05-08 10:00:00 UTC	34	13,2	91,8	2012-04-23 10:15:00 UTC	85	10,2	51,4
2002-05-09 08:40:00 UTC	33	13,2	91,8	2012-05-23 09:50:00 UTC	50	13,5	56,6
2002-05-23 11:00:00 UTC	43	13,2	91,8	2012-06-21 09:40:00 UTC	38	14,5	82,2
2002-06-05 09:30:00 UTC	104	14,5	135,8	2012-07-16 10:30:00 UTC	37	15,5	82,8
2002-06-05 09:45:00 UTC	104	14,5	135,8	2012-08-13 09:45:00 UTC	42	17,1	62,8
2002-06-20 09:30:00 UTC	128	14,5	135,8	2012-09-11 10:30:00 UTC	162	14,2	98
2002-07-05 11:00:00 UTC	88	15,3	100,2	2012-10-11 09:40:00 UTC	81	11,6	102,8
2002-07-10 11:30:00 UTC	135	15,3	100,2	2012-11-07 10:10:00 UTC	123	9,4	163
2002-07-18 10:15:00 UTC	119	15,3	100,2	2012-12-06 10:50:00 UTC	99	8	177,8
2002-08-01 09:10:00 UTC	214	16,8	36	2013-01-07 10:40:00 UTC	74	7,5	140,4
2002-08-08 10:40:00 UTC	96	16,8	36	2013-02-05 09:45:00 UTC	16	6,9	72
2002-08-14 09:50:00 UTC	47	16,8	36	2013-03-04 10:30:00 UTC	27	7	25
2002-08-30 10:15:00 UTC	161	16,8	36	2013-04-02 11:10:00 UTC	27	9,5	97,4
2002-09-12 09:35:00 UTC	96	16	80	2013-05-01 10:45:00 UTC	59	11,8	92,4
2002-09-13 09:35:00 UTC	98	16	80	2013-05-29 11:25:00 UTC	84	11,8	92,4
2002-09-26 10:30:00 UTC	46	16	80	2013-06-25 10:05:00 UTC	130	15,1	58,6
2002-10-11 11:00:00 UTC	75	11,6	118,8	2013-07-22 10:50:00 UTC	94	17,7	48
2002-10-11 11:20:00 UTC	73	11,6	118,8	2013-08-22 10:40:00 UTC	233	16,5	102,6
2002-10-24 09:40:00 UTC	109	11,6	118,8	2013-09-19 10:25:00 UTC	161	15,1	109,7
2002-11-05 10:30:00 UTC	106	10,8	136,8	2013-10-17 08:50:00 UTC	84	13,2	118
2002-11-05 10:45:00 UTC	104	10,8	136,8	2013-11-12 10:10:00 UTC	94	9,7	126,8
2002-11-21 10:05:00 UTC	49	10,8	136,8	2013-12-10 10:30:00 UTC	37	9,5	219,4
2002-12-05 10:45:00 UTC	87	8,2	52	2014-01-27 10:35:00 UTC	47	7,9	187,4
2002-12-18 08:30:00 UTC	29	8,2	52	2014-03-03 11:00:00 UTC	78	9,4	100,6
2003-01-16 11:05:00 UTC	53	7,8	100,8	2014-03-21 09:20:00 UTC	78	9,4	100,6
2003-02-11 09:20:00 UTC	42	7,7	55,6	2014-04-07 08:37:00 UTC	95	12,1	48
2003-03-12 10:15:00 UTC	50	9,8	78	2014-05-06 11:35:00 UTC	126	13,3	110
2004-02-20 09:15:00 UTC	38	8,1	54	2014-06-16 10:10:00 UTC	231	15,7	47,4
2004-03-19 09:40:00 UTC	48	9,4	86,2	2014-06-24 09:00:00 UTC	107	15,7	47,4

2004-04-16 08:15:00 UTC	103	11	79,6	2014-07-16 11:25:00 UTC	198	17,7	118,2
2004-05-14 09:25:00 UTC	73	13,1	34,6	2014-08-29 10:49:00 UTC	140	16	100,6
2004-06-11 09:45:00 UTC	150	14,9	68,2	2014-09-26 11:10:00 UTC	169	16,1	27
2004-07-07 08:16:00 UTC	206	16,1	75,2	2014-10-30 09:25:00 UTC	62	13,3	250,4
2004-09-01 11:11:00 UTC	107	15,4	192,8	2014-11-12 11:05:00 UTC	94	11,4	128,4
2004-09-28 11:00:00 UTC	117	15,4	192,8	2014-11-27 09:20:00 UTC	135	11,4	128,4
2004-10-29 09:38:00 UTC	92	12,6	143,3	2014-12-02 10:15:00 UTC	140	8,7	186,8
2004-11-24 09:20:00 UTC	107	10,6	93,6	2015-01-12 10:40:00 UTC	10	7,6	177,6
2004-12-21 10:50:00 UTC	62	9,7	145,8	2015-02-10 08:36:00 UTC	24	7,6	96,4
2005-01-05 09:25:00 UTC	40	9,2	148,3	2015-03-09 10:25:00 UTC	42	8,8	140,6
2005-01-31 09:05:00 UTC	14	9,2	148,3	2015-04-07 08:10:00 UTC	31	10,4	60,6
2005-03-04 09:00:00 UTC	28	10	83,6	2015-05-07 09:20:00 UTC	77	11,3	123,4
2005-03-31 10:15:00 UTC	53	10	83,6	2015-05-18 10:30:00 UTC	81	11,3	123,4
2005-04-29 09:00:00 UTC	78	11,2	109,2	2015-06-01 08:25:00 UTC	105	13,2	68,8
2005-05-25 08:55:00 UTC	67	12,3	86	2015-07-06 08:40:00 UTC	225	15,1	165,8
2005-06-24 10:30:00 UTC	175	15,3	85,8	2015-07-31 09:15:00 UTC	167	15,1	165,8
2005-07-22 08:50:00 UTC	217	16,2	39,2	2015-08-19 08:35:00 UTC	135	15,9	74,7
2005-08-17 08:40:00 UTC	129	16,4	119	2015-08-21 09:50:00 UTC	222	15,9	74,7
2005-09-13 09:35:00 UTC	158	15,8	140	2015-08-26 11:05:00 UTC	126	15,9	74,7
2005-10-11 09:15:00 UTC	64		126	2015-09-16 10:30:00 UTC	152	14,7	40,9
2005-11-09 09:50:00 UTC	32	10,3	109,8	2015-09-16 10:40:00 UTC	149	14,7	40,9
2005-12-08 09:30:00 UTC	18	9,1	111,4	2015-09-22 09:45:00 UTC	5	14,7	40,9
2006-01-11 09:50:00 UTC	52	8,5	76,6	2015-09-22 09:45:00 UTC	184	14,7	40,9
2006-02-09 09:20:00 UTC	70	8,3	59	2015-10-20 10:35:00 UTC	132	13,5	73,8
2006-03-07 10:00:00 UTC	69	7,9	114,4	2015-10-27 10:15:00 UTC	96	13,5	73,8
2006-04-04 09:15:00 UTC	49		81,2	2015-11-02 11:00:00 UTC	99	10,7	189,6
2006-05-03 09:40:00 UTC	70	12,8	98,8	2015-11-03 10:10:00 UTC	102	10,7	189,6
2006-05-30 10:40:00 UTC	92	12,8	98,8	2015-11-09 12:30:00 UTC	106	10,7	189,6
2006-06-30 10:30:00 UTC	119	15,2	69	2015-11-10 08:30:00 UTC	97	10,7	189,6
2006-07-28 09:10:00 UTC	76	17,7	82,2	2015-11-16 12:45:00 UTC	58	10,7	189,6
2006-08-23 09:55:00 UTC	96	16,4	65,6	2015-12-03 08:44:00 UTC	56	9,8	268,6
2006-09-22 09:15:00 UTC	160	16,4	123,2	2015-12-10 10:10:00 UTC	40	9,8	268,6
2006-10-19 08:55:00 UTC	161	14,1	184,6	2015-12-15 09:15:00 UTC	39	9,8	268,6
2006-11-16 09:15:00 UTC	45	10,7	136,4	2016-01-28 10:06:00 UTC	82	8	186,2
2006-12-14 09:30:00 UTC	36	9,5	178	2016-01-28 10:10:00 UTC	81	8	186,2
2007-01-11 09:45:00 UTC	47			2016-02-12 09:20:00 UTC	17	7,4	153,6
2007-02-05 09:55:00 UTC	52	8,4	106	2016-02-15 11:00:00 UTC	18	7,4	153,6
2007-03-09 09:30:00 UTC	60	9,3	76,6	2016-03-08 08:10:00 UTC	35	8,9	92,4
2007-04-05 10:25:00 UTC	36	12,3	46,8	2016-04-18 10:35:00 UTC	63	9,5	77,4
2007-05-04 10:10:00 UTC	46	12,8	69,8	2016-05-09 10:00:00 UTC	91	14,3	60,2
2007-05-30 11:00:00 UTC	52	12,8	69,8				

Ätran

Table 9.5-6. Date, colour, temperature and rainfall for Ätran for all the available colour observations in Ätran. Temperature and rainfall values were found by pre-processing downloaded hourly and daily observations, respectively.

Date	Colour	Temperature	Rainfall	Date	Colour	Temperature	Rainfall
2000-02-07 00:00:00 UTC	80	3,463095238	59	2006-08-10 00:00:00 UTC	55	16,98214286	38,3
2000-04-10 00:00:00 UTC	70	3,564285714	4,4	2006-10-16 00:00:00 UTC	200	9,170238095	0
2000-06-14 00:00:00 UTC	90	13,7125	2,9	2006-12-12 00:00:00 UTC	140	6,366666667	108,4
2000-08-17 00:00:00 UTC	80	14,72321429	8,7	2007-02-23 00:00:00 UTC	90	-1,685119048	9,2
2000-10-18 00:00:00 UTC	70	9,730952381	8,5	2007-04-19 00:00:00 UTC	80	8,463095238	30,4
2000-12-11 00:00:00 UTC	110	6,891666667	16,5	2007-06-12 00:00:00 UTC	65	19,80714286	2,6
2001-02-12 00:00:00 UTC	80	0,869642857	51,2	2007-08-08 00:00:00 UTC	90	16,41904762	4,9
2001-04-19 00:00:00 UTC	80	0,94702381	23,2	2007-10-02 00:00:00 UTC	280	10,19642857	33
2001-06-11 00:00:00 UTC	70	9,480357143	21,9	2007-12-03 00:00:00 UTC	120	2,764285714	59,3
2001-08-20 00:00:00 UTC	70	17,4577381	3	2008-02-13 00:00:00 UTC	80	2,941666667	2
2001-10-15 00:00:00 UTC	140	12,01904762	51,9	2008-04-14 00:00:00 UTC	90	3,377380952	8,9
2001-12-10 00:00:00 UTC	100	2,363095238	6,4	2008-06-09 00:00:00 UTC	60	17,49047619	0
2002-02-11 00:00:00 UTC	80	5,088690476	66,2	2008-08-13 00:00:00 UTC	80	15,97797619	74,4
2002-04-08 00:00:00 UTC	50	4,302380952	0,1	2008-10-15 00:00:00 UTC	180	10,90654762	49,5
2002-06-13 00:00:00 UTC	80	14,44880952	25,3	2008-12-03 00:00:00 UTC	120	3,117857143	52,7
2002-08-22 00:00:00 UTC	140	18,21607143	0	2009-02-12 00:00:00 UTC	50	-0,280357143	8
2002-10-07 00:00:00 UTC	60	8,063690476	10,8	2009-04-14 00:00:00 UTC	80	8,32797619	6,1
2002-12-19 00:00:00 UTC	85	-3,339880952	1,1	2009-06-08 00:00:00 UTC	60	9,204761905	3,3
2003-02-10 00:00:00 UTC	85	-4,211309524	2,9	2009-08-04 00:00:00 UTC	120	15,99642857	40
2003-04-07 00:00:00 UTC	60	1,711309524	12	2009-10-06 00:00:00 UTC	100	6,219047619	58,6
2003-06-23 00:00:00 UTC	70	13,51845238	31,9	2009-12-08 00:00:00 UTC	120	2,59702381	10,4
2003-08-12 00:00:00 UTC	100	18,375	0	2010-02-16 00:00:00 UTC	50	-5,620833333	3,3
2003-10-06 00:00:00 UTC	50	6,625595238	21,3	2010-04-13 00:00:00 UTC	80	6,256547619	0,4
2003-12-15 00:00:00 UTC	120	1,80297619	30,8	2010-06-08 00:00:00 UTC	60	13,66666667	15,3
2004-02-23 00:00:00 UTC	90	-2,151785714	2,6	2010-08-19 00:00:00 UTC	140	17,66547619	33,3
2004-04-26 00:00:00 UTC	65	7,344642857	11,4	2010-10-13 00:00:00 UTC	90	6,030357143	2,4
2004-06-16 00:00:00 UTC	50	12,98392857	21,3	2010-12-14 00:00:00 UTC	70	-5,271428571	4,8

2004-08-31 00:00:00 UTC	120	13,23809524	37,3	2011-02-15 00:00:00 UTC	90	-3,598809524	12,3
2004-10-24 00:00:00 UTC	180	8,833333333	62,6	2011-04-06 00:00:00 UTC	70	5,649404762	33,2
2004-12-16 00:00:00 UTC	100	4,147619048	50,5	2011-06-08 00:00:00 UTC	60	17,33571429	9,5
2005-02-23 00:00:00 UTC	70	-1,9625	10,2	2011-08-24 00:00:00 UTC	160	13,84642857	26,6
2005-04-25 00:00:00 UTC	70	4,129761905	1,2	2011-10-13 00:00:00 UTC	150	6,970238095	28,5
2005-06-27 00:00:00 UTC	70	15,00059524	5,6	2011-12-07 00:00:00 UTC	120	2,725595238	49
2005-08-31 00:00:00 UTC	150	13,02321429	36,6	2013-02-26 00:00:00 UTC	85,09654	-3,813690476	0,1
2005-10-24 00:00:00 UTC	70	5,364285714	42,2	2013-04-19 00:00:00 UTC	78,52732	7,057738095	23,6
2005-12-15 00:00:00 UTC	125	2,391071429	9,4	2013-06-14 00:00:00 UTC	91,04012	13,00535714	28,5
2006-02-14 00:00:00 UTC	70	-1,285714286	3,3	2013-08-16 00:00:00 UTC	83,53244	13,83333333	53,4
2006-04-05 00:00:00 UTC	100	2,570238095	30,7	2013-10-15 00:00:00 UTC	71,9581	8,793452381	22,1
2006-06-14 00:00:00 UTC	90	16,30535714	0,1	2013-12-16 00:00:00 UTC	121,38366	4,954166667	30,9

Päijänne

Table 9.5-7. Date, colour, temperature and rainfall for Päijänne, for all the dates where colour observations in Päijänne were available. Empty fields appear when observations of temperature are lacking.

Date	Colour	Temperature	Rainfall	Date	Colour	Temperature	Rainfall
2001-07-03 00:00:00 UTC	18		133,3	2008-08-11 00:00:00 UTC	20	12,7	132,4
2002-02-12 00:00:00 UTC	18	-3,1	47,4	2009-01-20 00:00:00 UTC	20	-7	35,7
2003-02-11 00:00:00 UTC	15	-7,4	9,2	2009-03-17 00:00:00 UTC	15	-3,3	19,8
2003-08-12 00:00:00 UTC	12		90,1	2009-05-12 00:00:00 UTC	20	10,6	16,3
2004-02-10 00:00:00 UTC	12	-7,2	38,9	2009-07-07 00:00:00 UTC	20	15,7	126,3
2004-04-20 00:00:00 UTC	13	3,2	14,5	2009-09-15 00:00:00 UTC	15	10,6	40,8
2004-06-08 00:00:00 UTC	15	12	82,4	2009-11-17 00:00:00 UTC	15	0,7	54,7
2004-08-10 00:00:00 UTC	20	14,8	75,1	2010-02-09 00:00:00 UTC	20	-11,1	46,6
2004-10-12 00:00:00 UTC	15	3,6	38,7	2010-04-13 00:00:00 UTC	15	3,5	42
2004-12-14 00:00:00 UTC	20	-2,6	70,6	2010-06-01 00:00:00 UTC	25	13,4	38
2005-02-15 00:00:00 UTC	15	-7,7	10,6	2010-08-17 00:00:00 UTC	20	16,2	43,8
2005-04-12 00:00:00 UTC	20		9,4	2010-10-12 00:00:00 UTC	25	3,3	43
2005-06-07 00:00:00 UTC	20		67,2	2010-12-14 00:00:00 UTC	20	-13,2	35,4
2005-08-16 00:00:00 UTC	20	14,7	102,2	2011-03-15 00:00:00 UTC	20	-3,1	19,9
2005-10-11 00:00:00 UTC	20	5,4	46	2011-06-14 00:00:00 UTC	20	16	56,1
2005-12-13 00:00:00 UTC	15	-5,5	67,3	2011-09-27 00:00:00 UTC	20	11,2	149,3
2006-02-06 00:00:00 UTC	15		14,6	2011-12-13 00:00:00 UTC	22	0,2	32,4
2006-04-04 00:00:00 UTC	13	2,8	48,1	2012-03-20 00:00:00 UTC	20	-1,8	46,9
2006-06-06 00:00:00 UTC	15	15	43,6	2012-06-12 00:00:00 UTC	25	12,6	86,6
2006-08-22 00:00:00 UTC	12	17	55,6	2012-09-18 00:00:00 UTC	30	9,6	121,7
2006-10-10 00:00:00 UTC	15	5,2	152,8	2012-12-11 00:00:00 UTC	25	-10,9	86,9
2006-12-12 00:00:00 UTC	15	1,1	59,2	2013-04-03 00:00:00 UTC	20	1,7	37
2007-02-13 00:00:00 UTC	20	-14	25,1	2013-07-23 00:00:00 UTC	30	15,2	50,1
2007-04-17 00:00:00 UTC	15		33,1	2013-09-24 00:00:00 UTC	25	10,2	59,2
2007-06-05 00:00:00 UTC	15	13,9	81	2013-11-26 00:00:00 UTC	25	1,5	86,7
2007-08-14 00:00:00 UTC	15	15,6	87,8	2014-02-18 00:00:00 UTC	25	-1,3	21,3
2007-10-09 00:00:00 UTC	15	5,2	54,3	2014-06-10 00:00:00 UTC	30	12,1	67,2
2007-12-10 00:00:00 UTC	15	-0,2	64,5	2014-09-30 00:00:00 UTC	27	10,4	37
2008-02-11 00:00:00 UTC	15	-2,4	59,5	2014-11-18 00:00:00 UTC	27	0,1	34,3
2008-06-10 00:00:00 UTC	20	12,9	91,3	2015-01-20 00:00:00 UTC	26	-5,9	66,6

9.5.3 NDVI

Here the regional mean NDVI values are shown for the six catchments. That is, for every date with NetCDF file with NDVI data, the computed mean of all NDVI values associated with the geographical locations constituting every catchment, are shown. The tables provided are Table 9.5-8 (Jordalsvatnet), Table 9.5-9 (Glomma), Table 9.5-10 (Port Charlotte), Table 9.5-11 (Bracadale), Table 9.5-12 (Ätran), Table 9.5-13 (Päijänne).

Jordalsvatnet

Table 9.5-8. Date and corresponding computed mean NDVI value for Jordalsvatnet.

Date	NDVI	Date	NDVI	Date	NDVI
1999-06-01	0,646666667	2004-08-01	0,710888889	2010-07-01	0,763111153
1999-06-11	0,498769231	2004-08-11	0,772222222	2010-07-11	0,654666667
1999-06-21	0,570444444	2004-08-21	0,555777778	2010-07-21	0,700222222
1999-07-01	0,703333333	2005-06-01	0,425	2010-08-01	0,675555593
1999-07-11	0,707058824	2005-06-11	0,535555556	2010-08-11	0,709555556
1999-07-21	0,761333333	2005-06-21	0,708	2010-08-21	0,681555556
1999-08-01	0,716	2005-07-01	0,746444444	2011-06-01	0,699555556
1999-08-11	0,66	2005-07-11	0,713777778	2011-06-11	0,715111111
1999-08-21	0,731777778	2005-07-21	0,755111111	2011-06-21	0,546666667
2000-06-01	0,690666667	2005-08-01	0,634666667	2011-07-01	0,568222222
2000-06-11	0,671111111	2005-08-11	0,643777778	2011-07-11	0,563555556
2000-06-21	0,638	2005-08-21	0,558	2011-07-21	0,446888889
2000-07-01	0,638	2006-06-01	0,643111111	2011-08-01	0,572235294
2000-07-11	0,671333333	2006-06-11	0,696	2011-08-11	0,705555556
2000-07-21	0,675333333	2006-06-21	0,655333333	2011-08-21	0,639111111
2000-08-01	0,694222222	2006-07-01	0,613777778	2012-06-01	0,620888889
2000-08-11	0,535555556	2006-07-11	0,736222222	2012-06-11	0,622444444
2000-08-21	0,665333333	2006-07-21	0,708444444	2012-06-21	0,624888889
2001-06-01	0,528470588	2006-08-01	0,68	2012-07-01	0,667555556
2001-06-11	0,548444444	2006-08-11	0,661555556	2012-07-11	0,6684
2001-06-21	0,607333333	2006-08-21	0,674666667	2012-07-21	0,536941176
2001-07-01	0,554222222	2007-06-01	0,682	2012-08-01	0,429066667
2001-07-11	0,53625	2007-06-11	0,716888889	2012-08-11	0,741333333
2001-07-21	0,625777778	2007-06-21	0,685333333	2012-08-21	0,780222222
2001-08-01	0,6495	2007-07-01	0,601176471	2013-06-01	0,613555556
2001-08-11	0,498	2007-07-11	0,519733333	2013-06-11	0,680888889
2001-08-21	0,636666667	2007-07-21	0,518	2013-06-21	0,671111111
2002-06-01	0,68	2007-08-01	0,746117647	2013-07-01	0,668222222
2002-06-11	0,692444444	2007-08-11	0,729	2013-07-11	0,636222222
2002-06-21	0,654888889	2007-08-21	0,673176471	2013-07-21	0,760666667
2002-07-01	0,613142857	2008-06-01	0,689555556	2013-08-01	0,592666667
2002-07-11	0,563555556	2008-06-11	0,723333333	2013-08-11	0,522588235
2002-07-21	0,592222222	2008-06-21	0,704	2013-08-21	0,739111111
2002-08-01	0,716444444	2008-07-01	0,798222266	2014-06-01	0,686
2002-08-11	0,613555556	2008-07-11	0,670222222	2014-06-11	0,722888889
2002-08-21	0,653777778	2008-07-21	0,775555556	2014-06-21	0,719294118
2003-06-01	0,644444444	2008-08-01	0,76777782	2014-07-01	0,742
2003-06-11	0,670222222	2008-08-11	0,676	2014-07-11	0,653333333
2003-06-21	0,730666667	2008-08-21	0,654	2014-07-21	0,704666667
2003-07-01	0,736666667	2009-06-01	0,745111152	2014-08-01	0,648857143
2003-07-11	0,745333333	2009-06-11	0,598222222	2014-08-11	0,605
2003-07-21	0,660444444	2009-06-21	0,687555556	2014-08-21	0,773454545
2003-08-01	0,668444444	2009-07-01	0,768888931	2015-06-01	0,45
2003-08-11	0,706444444	2009-07-11	0,714666667	2015-06-11	0,5504
2003-08-21	0,700666667	2009-07-21	0,4912	2015-06-21	0,584470588
2004-06-01	0,637777778	2009-08-01	0,660666704	2015-07-01	0,602
2004-06-11	0,513777778	2009-08-11	0,437454545	2015-07-11	0,631555556
2004-06-21	0,607111111	2009-08-21	0,3892	2015-07-21	0,601428571
2004-07-01	0,706888889	2010-06-01	0,726444485	2015-08-01	0,641176471
2004-07-11	0,681333333	2010-06-11	0,686222222	2015-08-11	0,743555556
2004-07-21	0,618888889	2010-06-21	0,685777778	2015-08-21	0,74125

Glomma

Table 9.5-9. Date and corresponding computed mean NDVI value for Glomma.

Date	NDVI	Date	NDVI	Date	NDVI
1999-06-01	0,425445061	2004-07-01	0,523197756	2009-08-01	0,691043461
1999-06-11	0,506617706	2004-07-11	0,54919647	2009-08-11	0,559503239
1999-06-21	0,520329608	2004-07-21	0,584038661	2009-08-21	0,549127938
1999-07-01	0,601874949	2004-08-01	0,609604862	2010-06-01	
1999-07-11	0,615782941	2004-08-11	0,641000025	2010-06-11	0,494158376
1999-07-21	0,61608249	2004-08-21	0,549691158	2010-06-21	0,529008071
1999-08-01	0,64427802	2005-06-01	0,442045691	2010-07-01	0,685176417
1999-08-11	0,582811059	2005-06-11	0,529136263	2010-07-11	0,572772306
1999-08-21	0,558448572	2005-06-21	0,577482708	2010-07-21	0,634168782
2000-06-01	0,509890809	2005-07-01	0,580037664	2010-08-01	
2000-06-11	0,506619865	2005-07-11	0,594061375	2010-08-11	0,59240965
2000-06-21	0,502680018	2005-07-21	0,56614805	2010-08-21	0,57188558
2000-07-01	0,510342279	2005-08-01	0,556355598	2011-06-01	0,50623255
2000-07-11	0,51308961	2005-08-11	0,577057125	2011-06-11	0,495408761
2000-07-21	0,607030996	2005-08-21	0,593039902	2011-06-21	0,523109314
2000-08-01	0,586749197	2006-06-01	0,466710222	2011-07-01	0,518630997
2000-08-11	0,559408234	2006-06-11	0,522196464	2011-07-11	0,573481314
2000-08-21	0,558030032	2006-06-21	0,55229458	2011-07-21	0,547387339
2001-06-01	0,411726824	2006-07-01	0,57905621	2011-08-01	0,530642846
2001-06-11	0,437605074	2006-07-11	0,62526879	2011-08-11	0,573141968
2001-06-21	0,490164699	2006-07-21	0,569832268	2011-08-21	0,507954049
2001-07-01	0,580209838	2006-08-01	0,57831975	2012-06-01	0,473996707
2001-07-11	0,586839477	2006-08-11	0,538913291	2012-06-11	0,489533309
2001-07-21	0,564912796	2006-08-21	0,562236746	2012-06-21	0,519481784
2001-08-01	0,553968986	2007-06-01	0,535030291	2012-07-01	0,564646971
2001-08-11	0,554794167	2007-06-11	0,587650068	2012-07-11	0,510315557
2001-08-21	0,557509937	2007-06-21	0,584293637	2012-07-21	0,522751433
2002-06-01	0,532166642	2007-07-01	0,549573511	2012-08-01	0,534798969
2002-06-11	0,528417197	2007-07-11	0,542042449	2012-08-11	0,621178011
2002-06-21	0,514843917	2007-07-21	0,60715171	2012-08-21	0,607673821
2002-07-01	0,514451208	2007-08-01	0,54829501	2013-06-01	0,455718037
2002-07-11	0,554956265	2007-08-11	0,545756993	2013-06-11	0,532518334
2002-07-21	0,566907805	2007-08-21	0,60894815	2013-06-21	0,518115493
2002-08-01	0,580294758	2008-06-01	0,501442244	2013-07-01	0,565210542
2002-08-11	0,564938264	2008-06-11	0,52804448	2013-07-11	0,594324296
2002-08-21	0,553437673	2008-06-21	0,546425774	2013-07-21	0,64822633
2003-06-01	0,470006138	2008-07-01	0,708124887	2013-08-01	0,596578112
2003-06-11	0,481463435	2008-07-11	0,577173751	2013-08-11	0,605407354
2003-06-21	0,51693457	2008-07-21	0,653082713	2013-08-21	0,608086713
2003-07-01	0,60541832	2008-08-01	0,842973376	2014-06-01	0,477899512
2003-07-11	0,626499275	2008-08-11	0,515676028	2014-06-11	0,536390534
2003-07-21	0,584591249	2008-08-21	0,535232275	2014-06-21	0,533520854
2003-08-01	0,61995064	2009-06-01		2014-07-01	0,553351299
2003-08-11	0,620979522	2009-06-11	0,468948326	2014-07-11	0,601915592
2003-08-21	0,542782923	2009-06-21	0,565396837	2014-07-21	0,609077831
2004-06-01	0,504270848	2009-07-01	0,697216128	2014-08-01	0,559494401
2004-06-11	0,493711278	2009-07-11	0,53573521	2014-08-11	0,539053322
2004-06-21	0,498214852	2009-07-21	0,541058796	2014-08-21	0,579645903

Port Charlotte

Table 9.5-10. Date and corresponding computed mean NDVI value for Port Charlotte.

Date	NDVI	Date	NDVI	Date	NDVI
1999-06-01	0,6245	2004-08-01	0,769	2010-07-01	0,758000042
1999-06-11	0,622	2004-08-11	0,661	2010-07-11	0,6165
1999-06-21	0,649	2004-08-21	0,7	2010-07-21	0,7595
1999-07-01	0,7205	2005-06-01	0,588	2010-08-01	0,73100004
1999-07-11	0,744	2005-06-11	0,645	2010-08-11	0,674
1999-07-21	0,767	2005-06-21	0,698	2010-08-21	0,715
1999-08-01	0,721	2005-07-01	0,678	2011-06-01	0,659
1999-08-11	0,708	2005-07-11	0,7075	2011-06-11	0,6285
1999-08-21	0,66	2005-07-21	0,739	2011-06-21	0,586285714
2000-06-01	0,616	2005-08-01	0,6585	2011-07-01	0,61
2000-06-11	0,567	2005-08-11	0,694	2011-07-11	0,7335
2000-06-21	0,53	2005-08-21	0,753	2011-07-21	0,7465

2000-07-01	0,5895	2006-06-01	0,6065	2011-08-01	0,59
2000-07-11	0,645	2006-06-11	0,66	2011-08-11	0,6175
2000-07-21	0,6015	2006-06-21	0,707	2011-08-21	0,6575
2000-08-01	0,7	2006-07-01	0,662	2012-06-01	0,593
2000-08-11	0,681	2006-07-11	0,7665	2012-06-11	0,5695
2000-08-21	0,7055	2006-07-21	0,7125	2012-06-21	0,6064
2001-06-01	0,64	2006-08-01	0,7	2012-07-01	
2001-06-11	0,6455	2006-08-11	0,624	2012-07-11	0,6075
2001-06-21	0,683	2006-08-21	0,5425	2012-07-21	0,5655
2001-07-01	0,624	2007-06-01	0,664	2012-08-01	0,7205
2001-07-11	0,729	2007-06-11	0,719	2012-08-11	0,764
2001-07-21	0,652	2007-06-21	0,6255	2012-08-21	0,703
2001-08-01	0,6595	2007-07-01	0,5985	2013-06-01	0,574
2001-08-11	0,5985	2007-07-11	0,6565	2013-06-11	0,6005
2001-08-21	0,684	2007-07-21	0,708	2013-06-21	0,6295
2002-06-01	0,5725	2007-08-01	0,6465	2013-07-01	0,699
2002-06-11	0,699	2007-08-11	0,711	2013-07-11	0,681
2002-06-21	0,7085	2007-08-21	0,761	2013-07-21	0,687
2002-07-01	0,658	2008-06-01	0,681	2013-08-01	0,7005
2002-07-11	0,6775	2008-06-11	0,69	2013-08-11	0,683
2002-07-21	0,687	2008-06-21	0,755	2013-08-21	0,602
2002-08-01	0,6765	2008-07-01	0,760000042	2014-06-01	0,646
2002-08-11	0,6465	2008-07-11	0,6705	2014-06-11	0,733
2002-08-21	0,679	2008-07-21	0,764	2014-06-21	0,7265
2003-06-01	0,6535	2008-08-01	0,71900004	2014-07-01	0,7905
2003-06-11	0,6095	2008-08-11	0,704	2014-07-11	0,7795
2003-06-21	0,707	2008-08-21	0,7585	2014-07-21	0,7745
2003-07-01	0,675	2009-06-01	0,741000041	2014-08-01	0,782
2003-07-11	0,744	2009-06-11	0,708	2014-08-11	0,764
2003-07-21	0,702	2009-06-21	0,6925	2014-08-21	0,7185
2003-08-01	0,624	2009-07-01	0,779500043	2015-06-01	0,6005
2003-08-11	0,622	2009-07-11	0,713	2015-06-11	0,6705
2003-08-21	0,6735	2009-07-21	0,693	2015-06-21	0,5845
2004-06-01	0,5725	2009-08-01	0,788000043	2015-07-01	0,7225
2004-06-11	0,5935	2009-08-11	0,5995	2015-07-11	0,7565
2004-06-21	0,6895	2009-08-21	0,59	2015-07-21	0,7195
2004-07-01	0,7345	2010-06-01	0,661500037	2015-08-01	0,76
2004-07-11	0,7335	2010-06-11	0,693	2015-08-11	0,764
2004-07-21	0,736	2010-06-21	0,648	2015-08-21	0,7515

Bracadale

Table 9.5-11. Date and corresponding computed mean NDVI value for Bracadale.

Date	NDVI	Date	NDVI	Date	NDVI
2000-06-01	0,6475	2005-08-01	0,6545	2011-07-01	0,615
2000-06-11	0,6485	2005-08-11	0,7185	2011-07-11	0,724
2000-06-21	0,612	2005-08-21	0,6995	2011-07-21	0,683
2000-07-01	0,604	2006-06-01	0,6375	2011-08-01	0,7165
2000-07-11	0,6475	2006-06-11	0,626	2011-08-11	0,5816
2000-07-21	0,72	2006-06-21	0,639	2011-08-21	0,6205
2000-08-01	0,624	2006-07-01	0,634	2012-06-01	0,634
2000-08-11	0,693	2006-07-11	0,7085	2012-06-11	0,6715
2000-08-21	0,6	2006-07-21	0,6335	2012-06-21	0,688
2001-06-01	0,601	2006-08-01	0,548	2012-07-01	0,729
2001-06-11	0,641142857	2006-08-11	0,723	2012-07-11	0,685
2001-06-21	0,6605	2006-08-21	0,636	2012-07-21	0,6665
2001-07-01	0,62	2007-06-01	0,656	2012-08-01	0,723
2001-07-11	0,6495	2007-06-11	0,67	2012-08-11	0,6975
2001-07-21	0,6855	2007-06-21	0,609333333	2012-08-21	0,6505
2001-08-01	0,662	2007-07-01	0,584	2013-06-01	0,6275
2001-08-11	0,621	2007-07-11	0,69	2013-06-11	0,627428571
2001-08-21	0,598	2007-07-21	0,6495	2013-06-21	0,624
2002-06-01	0,611	2007-08-01	0,6835	2013-07-01	0,723
2002-06-11	0,618857143	2007-08-11	0,7235	2013-07-11	0,758
2002-06-21	0,574666667	2007-08-21	0,7705	2013-07-21	0,7655
2002-07-01	0,707	2008-06-01	0,587	2013-08-01	0,653
2002-07-11	0,6905	2008-06-11	0,559	2013-08-11	0,616
2002-07-21	0,7045	2008-06-21	0,557	2013-08-21	0,608
2002-08-01	0,7135	2008-07-01	0,72500004	2014-06-01	0,559428571
2002-08-11	0,7325	2008-07-11	0,5815	2014-06-11	0,5528
2002-08-21	0,715	2008-07-21	0,696	2014-06-21	0,7695
2003-06-01	0,529	2008-08-01	0,774500042	2014-07-01	0,794
2003-06-11	0,544571429	2008-08-11	0,756571429	2014-07-11	0,7975

2003-06-21	0,698	2008-08-21	0,644571429	2014-07-21	0,724
2003-07-01	0,738	2009-06-01	0,745000041	2014-08-01	0,6715
2003-07-11	0,7505	2009-06-11	0,5975	2014-08-11	0,6912
2003-07-21	0,6552	2009-06-21	0,66	2014-08-21	0,766
2003-08-01	0,688	2009-07-01	0,72300004	2015-06-01	0,4424
2003-08-11	0,7145	2009-07-11	0,71	2015-06-11	0,545
2003-08-21	0,7015	2009-07-21	0,688	2015-06-21	
2004-06-01	0,629	2009-08-01	0,71500004	2015-07-01	0,64
2004-06-11	0,568	2009-08-11	0,64	2015-07-11	0,6425
2004-06-21	0,714	2009-08-21	0,7125	2015-07-21	0,695
2004-07-01	0,675	2010-06-01	0,679500038	2015-08-01	0,706
2004-07-11	0,61	2010-06-11	0,668	2015-08-11	0,6895
2004-07-21	0,725	2010-06-21	0,6985	2015-08-21	0,7115
2004-08-01	0,725	2010-07-01	0,696000039	2016-06-01	0,606
2004-08-11	0,752	2010-07-11	0,61	2016-06-11	0,638
2004-08-21	0,67	2010-07-21	0,6035	2016-06-21	0,6605
2005-06-01	0,6555	2010-08-01	0,742666708	2016-07-01	0,608
2005-06-11	0,681333333	2010-08-11	0,6825	2016-07-11	0,7325
2005-06-21	0,6725	2010-08-21	0,657142857	2016-07-21	
2005-07-01	0,662	2011-06-01	0,6125	2016-08-01	0,819428571
2005-07-11	0,7605	2011-06-11	0,6085	2016-08-11	0,709
2005-07-21	0,75	2011-06-21	0,6435	2016-08-21	0,697714286

Ätran

Table 9.5-12. Date and corresponding computed mean NDVI value for Bracadale.

Date	NDVI	Date	NDVI	Date	NDVI
1999-06-01	0,64550495	2004-06-01	0,64986102	2009-06-01	0,801155711
1999-06-11	0,690280872	2004-06-11	0,665828392	2009-06-11	0,632201719
1999-06-21	0,680932311	2004-06-21	0,642563407	2009-06-21	0,703349114
1999-07-01	0,777928829	2004-07-01	0,707841105	2009-07-01	0,783211831
1999-07-11	0,763409034	2004-07-11	0,69669628	2009-07-11	0,603185637
1999-07-21	0,67842295	2004-07-21	0,722528468	2009-07-21	0,594753313
1999-08-01	0,680335322	2004-08-01	0,705191209	2009-08-01	0,779437572
1999-08-11	0,597861268	2004-08-11	0,764469221	2009-08-11	0,704433879
1999-08-21	0,694876906	2004-08-21	0,627003584	2009-08-21	0,611285147
2000-06-01	0,667691488	2005-06-01	0,650057738	2010-06-01	0,769032806
2000-06-11	0,710279354	2005-06-11	0,696708247	2010-06-11	0,709572639
2000-06-21	0,675457574	2005-06-21	0,684007055	2010-06-21	0,702482521
2000-07-01	0,643973602	2005-07-01	0,701701539	2010-07-01	0,804906142
2000-07-11	0,608109744	2005-07-11	0,727720113	2010-07-11	0,689321837
2000-07-21	0,644499443	2005-07-21	0,622426511	2010-07-21	0,630349417
2000-08-01	0,624318869	2005-08-01	0,597638684	2010-08-01	0,752146773
2000-08-11	0,610128785	2005-08-11	0,713750243	2010-08-11	0,586301745
2000-08-21	0,660048912	2005-08-21	0,674645664	2010-08-21	0,630740814
2001-06-01	0,593358834	2006-06-01	0,648047656	2011-06-01	0,696338611
2001-06-11	0,560432653	2006-06-11	0,690881956	2011-06-11	0,626157078
2001-06-21	0,669015833	2006-06-21	0,63134786	2011-06-21	0,691423734
2001-07-01	0,739320897	2006-07-01	0,707667032	2011-07-01	0,670239554
2001-07-11	0,701408371	2006-07-11	0,769960809	2011-07-11	0,639516081
2001-07-21	0,732735683	2006-07-21	0,693515142	2011-07-21	0,58184509
2001-08-01	0,707304431	2006-08-01	0,669773319	2011-08-01	0,684124821
2001-08-11	0,690077963	2006-08-11	0,650878957	2011-08-11	0,66355139
2001-08-21	0,688128349	2006-08-21	0,58472106	2011-08-21	0,619786279
2002-06-01	0,706965193	2007-06-01	0,706678583	2012-06-01	0,602428097
2002-06-11	0,67901161	2007-06-11	0,727042483	2012-06-11	0,625792171
2002-06-21	0,653293204	2007-06-21	0,683438156	2012-06-21	0,644000719
2002-07-01	0,620570978	2007-07-01	0,612538979	2012-07-01	0,66271381
2002-07-11	0,646756255	2007-07-11	0,740108227	2012-07-11	0,661390454
2002-07-21	0,675838219	2007-07-21	0,674652069	2012-07-21	0,786938994
2002-08-01	0,655739144	2007-08-01	0,714989674	2012-08-01	0,735416549
2002-08-11	0,726589048	2007-08-11	0,680653682	2012-08-11	0,614870922
2002-08-21	0,663062549	2007-08-21	0,704800383	2012-08-21	0,655296749
2003-06-01	0,639142185	2008-06-01	0,723796833	2013-06-01	0,702723338
2003-06-11	0,603858107	2008-06-11	0,716869102	2013-06-11	0,679025553
2003-06-21	0,646525036	2008-06-21	0,607057195	2013-06-21	0,663190192
2003-07-01	0,642004909	2008-07-01	0,786616754	2013-07-01	0,709982756
2003-07-11	0,687042837	2008-07-11	0,61442269	2013-07-11	0,749212502
2003-07-21	0,604219815	2008-07-21	0,762456713	2013-07-21	0,762545854
2003-08-01	0,71228428	2008-08-01	0,797168879	2013-08-01	0,652802132
2003-08-11	0,667742158	2008-08-11	0,638661378	2013-08-11	0,633255309
2003-08-21	0,667908263	2008-08-21	0,700997646	2013-08-21	0,654518307

Päijänne

Table 9.5-13. Date and corresponding computed mean NDVI value for Päijänne.

Date	NDVI	Date	NDVI	Date	NDVI
2000-06-01	0,569308879	2005-07-01	0,73705655	2010-08-01	0,73961713
2000-06-11	0,586817849	2005-07-11	0,719306327	2010-08-11	0,699556664
2000-06-21	0,628911959	2005-07-21	0,688124769	2010-08-21	0,698260647
2000-07-01	0,627405169	2005-08-01	0,674733557	2011-06-01	0,689583233
2000-07-11	0,60787344	2005-08-11	0,656235452	2011-06-11	0,694010056
2000-07-21	0,669839506	2005-08-21	0,635449198	2011-06-21	0,684138013
2000-08-01	0,602141892	2006-06-01	0,525516366	2011-07-01	0,668812272
2000-08-11	0,602897976	2006-06-11	0,639460307	2011-07-11	0,622779338
2000-08-21	0,629859147	2006-06-21	0,60540819	2011-07-21	0,670604118
2001-06-01	0,562036861	2006-07-01	0,704854847	2011-08-01	0,712646961
2001-06-11	0,56050479	2006-07-11	0,712669909	2011-08-11	0,653985009
2001-06-21	0,697235825	2006-07-21	0,698370688	2011-08-21	0,551044344
2001-07-01	0,680981322	2006-08-01	0,693939626	2012-06-01	0,606058249
2001-07-11	0,613341479	2006-08-11	0,651814139	2012-06-11	0,634098569
2001-07-21	0,635372204	2006-08-21	0,589404528	2012-06-21	0,662891211
2001-08-01	0,588889518	2007-06-01	0,71728978	2012-07-01	0,676863549
2001-08-11	0,671602044	2007-06-11	0,633138538	2012-07-11	0,642888085
2001-08-21	0,627182949	2007-06-21	0,622413905	2012-07-21	0,623319693
2002-06-01	0,625965523	2007-07-01	0,638089713	2012-08-01	0,600786296
2002-06-11	0,597961689	2007-07-11	0,608406338	2012-08-11	0,629704114
2002-06-21	0,590805047	2007-07-21	0,608483204	2012-08-21	0,568577555
2002-07-01	0,607077941	2007-08-01	0,714579434	2013-06-01	0,603531243
2002-07-11	0,679668523	2007-08-11	0,644315523	2013-06-11	0,618609052
2002-07-21	0,687765524	2007-08-21	0,632720788	2013-06-21	0,622564592
2002-08-01	0,671770772	2008-06-01	0,644415272	2013-07-01	0,665636425
2002-08-11	0,662198828	2008-06-11	0,581153851	2013-07-11	0,697925457
2002-08-21	0,62589036	2008-06-21	0,569147371	2013-07-21	0,763896836
2003-06-01	0,500646318	2008-07-01	0,772285371	2013-08-01	0,66680796
2003-06-11	0,573174529	2008-07-11	0,604904311	2013-08-11	0,668081193
2003-06-21	0,641803794	2008-07-21	0,73526207	2013-08-21	0,711937333
2003-07-01	0,616171729	2008-08-01	0,709746928	2014-06-01	0,640531476
2003-07-11	0,667163513	2008-08-11	0,567050315	2014-06-11	0,671288852
2003-07-21	0,647282407	2008-08-21	0,513594372	2014-06-21	0,66039473
2003-08-01	0,655549558	2009-06-01	0,685077077	2014-07-01	0,701036546
2003-08-11	0,642836974	2009-06-11	0,561063236	2014-07-11	0,726579301
2003-08-21	0,640926423	2009-06-21	0,659552087	2014-07-21	0,71410588
2004-06-01	0,561556195	2009-07-01	0,781085554	2014-08-01	0,678316235
2004-06-11	0,561407805	2009-07-11	0,672429829	2014-08-11	0,668936837
2004-06-21	0,515738013	2009-07-21	0,639289825	2014-08-21	0,599880742
2004-07-01	0,565085399	2009-08-01	0,792533274	2015-06-01	0,589127598
2004-07-11	0,616045791	2009-08-11	0,608811246	2015-06-11	0,579688242
2004-07-21	0,689604436	2009-08-21	0,709816617	2015-06-21	0,642643676
2004-08-01	0,609742753	2010-06-01	0,739297951	2015-07-01	0,733424285
2004-08-11	0,653432613	2010-06-11	0,603944932	2015-07-11	0,693975208
2004-08-21	0,642084203	2010-06-21	0,643948209	2015-07-21	0,664737694
2005-06-01	0,540515258	2010-07-01	0,79908061	2015-08-01	0,680218209
2005-06-11	0,646644354	2010-07-11	0,703852926	2015-08-11	0,807896903
2005-06-21	0,657276649	2010-07-21	0,622554555	2015-08-21	0,790848387

9.5.4 Data for PCA

Here the data matrices used for performing the PCA´s are presented, for the six catchments, in Table 9.5-14 (Jordalsvatnet), Table 9.5-15 (Glomma), Table 9.5-16 (Port Charlotte), Table 9.5-17 (Bracadale), Table 9.5-18 (Ätran), Table 9.5-19 and (Päijänne).

Jordalsvatnet

Table 9.5-14. Pre-processed data for performing PCA for Jordalsvatnet.

	Colour	Rainfall	Temperature	NDVI	SO4
2000	16,22222	2395,9	8,8	0,666154	1130,074
2001	20,6	2089,7	7,7	0,653284	955,2295
2002	19,54545	2058,8	8,8	0,576074	950,1389
2003	20,83333	2628,7	8,8	0,642226	1055,776
2004	21,34483	2592,1	8,6	0,695926	976,176
2005	18,80345	3051,8	8,4	0,644963	1019,336
2006	21,38	2512,9	9,3	0,635593	825,1429
2007	18,36957	3018,1	8,4	0,674346	697,6135
2008	19,04878	2545,1	8,9	0,652381	622,2315
2009	20,10625	2092,5	8,6	0,71763	562,9093
2010	25,80435	1624,1	6,4	0,61033	468,2148
2011	25,25	2682,5	8,8	0,698123	623,8369
2012	22,13043	2632,6	7,8	0,606322	478,4838
2013	26,78	2469,5	8	0,632416	462,5908
2014	23,94118	2428,6	9,9	0,653893	739,5298
2015	24,44	3101,7	8,7	0,695055	454,9999

Glomma

Table 9.5-15. Pre-processed data for performing PCA for Glomma.

	Colour	Rainfall	Temperature	NDVI	SO4
2000	29,70588	610,7	5,3	0,541736	177,6733
2001	29,86275	478,7	3,4	0,511527	126,2601
2002	26,22	440,4	4	0,495722	119,2272
2003	28,76	431,5	4,2	0,531241	119,6611
2004	27,31915	460,1	4,4	0,552466	119,7884
2005	28,16327	367,7	5,2	0,52088	117,378
2006	31	486	5,4	0,529182	120,3278
2007	28	446,8	4,6	0,547264	70,95779
2008	34,4	518,4	5	0,552343	82,96169
2009	32,625	510,7	4,1	0,574738	78,20878
2010	32,08333	473,5	2,1	0,552927	74,49058
2011	29,36364	664,6	4,9	0,568933	71,50506

2012	33,08333	524,2	3,9	0,50954	60,10648
2013	24,09091	563,2	4,1	0,509079	45,41976
2014	31,08	469,2	6	0,559827	118,1819

Port Charlotte

Table 9.5-16. Pre-processed data for performing PCA for Port Charlotte.

	Colour	Rainfall	T_max	NDVI	SO4
2000	83	142,3	11,85833	0,690667	424,2292
2001	149,5116	140,3	11,69167	0,626167	417,2787
2002	104,4375	144,7	12,05833	0,657278	420,3005
2003	87,73684	147,6	12,3	0,667167	398,8842
2004	99,36364	147,5	12,29167	0,667833	297,8056
2005	109,5	133,5	12,13636	0,687722	298,6729
2006	95,53846	137,5	12,5	0,684556	307,0373
2007	79,64286	139,6	12,69091	0,664556	228,8542
2008	68	144,9	12,075	0,676667	229,6355
2009	114,1176	145,1	12,09167	0,722444	196,2703
2010	104,3125	134,7	11,225	0,7005	190,4897
2011	116,4706	145,2	12,1	0,695167	203,5499
2012	113,8421	141,5	11,79167	0,647643	176,6853
2013	89,5	139,5	11,625	0,641175	186,3754
2014	112,5	149,5	12,45833	0,650722	206,6255
2015	102,6667	138,6	11,55	0,746056	186,9178

Bracadale

Table 9.5-17. Pre-processed data for performing PCA for Bracadale.

	Colour	Rainfall	T_max	NDVI	SO4
2001	71,73016	140,3	11,69167	0,644056	310,5795
2002	66,65789	144,7	12,05833	0,637627	307,8387
2003	48,33333	147,6	12,3	0,674169	334,3337
2004	100,2727	147,5	12,29167	0,668808	298,3954
2005	82,53846	133,5	12,13636	0,674222	272,8766
2006	84,23077	137,5	12,5	0,694926	269,5965
2007	70,53846	139,6	12,69091	0,642833	213,763
2008	75,52	144,9	12,075	0,670704	203,2707
2009	81,8	145,1	12,09167	0,65346	185,1222
2010	86	134,7	11,225	0,687889	146,3056
2011	83	145,2	12,1	0,670868	197,2854
2012	70,53846	141,5	11,79167	0,645011	138,3821
2013	86,15385	139,5	11,625	0,682778	163,0646
2014	121,4286	149,5	12,45833	0,666937	191,4627

2015	98,46154	138,6	11,55	0,702881	185,1827
2016	55,28571	145,8	12,15	0,633988	132,4995

Ätran

Table 9.5-18. Pre-processed data for performing PCA for Ätran.

	Colour	Rainfall	Temperature	NDVI	SO4
2000	83,33333	1256,4	7,781665	0,68995	593,1002
2001	90	972,9	6,379982	0,64939	430,6806
2002	82,5	1078,3	7,182688	0,675754	452,6789
2003	80,83333	967,1	6,56468	0,669758	399,2575
2004	100,8333	1309,1	6,556544	0,652303	404,1522
2005	92,5	1034,2	6,635783	0,686887	358,9888
2006	109,1667	1404,1	7,359618	0,674295	361,3361
2007	120,8333	1370,2	7,785184	0,671866	291,3867
2008	101,6667	1535,7	7,679924	0,693878	289,9476
2009	88,33333	1020,7	6,914748	0,69386	258,801
2010	81,66667	1152,6	4,932705	0,690335	234,7899
2011	108,3333	1326,8	7,375156	0,690338	262,8936
2012	90,07982	1384,7	6,320954	0,652554	240,4659
2013	88,5897	968,6	6,598866	0,665428	190,5968

Päijänne

Table 9.5-19. Pre-processed data for performing PCA for Päijänne.

	Colour	Rainfall	Temperature	NDVI	SO4
2001	18	614,5	3,280675	0,613895	200,2406
2002	18	587,9	4,23619	0,62635	147,1607
2003	13,5	660,3	3,568889	0,638789	214,0314
2004	15,83333	701	3,766667	0,620617	157,6872
2005	18,33333	584,9	4,467143	0,601633	182,7596
2006	14,16667	598,2	4,587222	0,661705	151,7001
2007	15,83333	678,5	4,330357	0,646827	147,146
2008	18,33333	810,6	4,791667	0,646604	140,8569
2009	17,5	545,9	3,583333	0,633062	106,6243
2010	20,83333	538	2,6	0,678851	151,7702
2011	20,5	713,6	4,95	0,694457	116,6751
2012	25	769,7	3,041667	0,660845	126,5426
2013	25	668,2	4,683333	0,627243	82,17204
2014	27,25	608,9	4,958333	0,668777	132,7358
2015	26	629	5,341667	0,673452	95,98725

9.6 Appendix F Results of PCA

Here the loadings of all the principal components for the six PCA´s are shown, in Table 9.6-1 (Jordalsvatnet), Table 9.6-2 (Glomma), Table 9.6-3 (Port Charlotte), Table 9.6-4 (Bracadale), Table 9.6-5 (Ätran), Table 9.6-6 (Päijänne).

Jordalsvatnet

Table 9.6-1. The principal component loadings of the variables for Jordalsvatnet.

	PC1 (40.99 %)	**PC2 (28.78 %)**	**PC3 (13.11 %)**	**PC4 (11.15 %)**	**PC5 (5.958 %)**
Colour	0.5101473	-0.4106538	0.26516029	-0.3320272	0.6249489
Rainfall	-0.3940466	-0.4782323	0.41465457	0.6434562	0.1733405
Temperature	-0.5193924	-0.2105858	0.41282219	-0.6739144	-0.2475933
NDVI	-0.2754736	-0.5589792	-0.76353559	-0.1233549	0.1159893
SO4	-0.4886950	0.4958359	-0.06590033	-0.0796560	0.7103774

Glomma

Table 9.6-2. The principal component loadings of the variables for Glomma.

	PC1 (32.98 %)	**PC2 (27.55 %)**	**PC3 (18.68 %)**	**PC4 (11.75 %)**	**PC5 (9.033 %)**
Colour	0.5407074	-0.06867813	0.6130950	-0.3043015	0.48418379
Rainfall	0.4639854	-0.07907982	-0.7197518	-0.5063103	0.06380612
Temperature	0.1882045	0.69875780	-0.2320872	0.4521073	0.46695948
NDVI	0.6596416	0.07018551	0.1142290	0.3489868	-0.65200221
SO4	-0.1476653	0.70415995	0.1978867	-0.5699629	-0.34400118

Port Charlotte

Table 9.6-3. The principal component loadings of the variables for Port Charlotte.

	PC1 (34.34 %)	**PC2 (26.14 %)**	**PC3 (16.41 %)**	**PC4 (12.78 %)**	**PC5 (10.33 %)**
Colour	0.1096226	-0.6983348	0.48722056	-0.30669543	0.41093241
Rainfall	-0.5481296	0.1547873	0.53480033	-0.37115380	-0.50182493
Temperature	-0.5628114	0.3605704	0.03532701	0.02867252	0.74240297

NDVI	0.4543949	0.4592316	-0.04253152	-0.74674484	0.15229853
SO4	-0.4053460	-0.3840114	-0.68814810	-0.45796593	-0.07035118

Bracadale

Table 9.6-4. The principal component loadings of the variables for Bracadale.

	PC1 (38.81 %)	**PC2 (24.02 %)**	**PC3 (20.25 %)**	**PC4 (9.887 %)**	**PC5 (7.033 %)**
Colour	0.3533014	-0.6680233	0.32754096	0.02139852	0.5667292
Rainfall	-0.4827632	-0.2891650	0.48564954	-0.59890556	-0.2979597
Temperature	-0.5081524	-0.4425261	-0.02916128	0.70641662	-0.2146556
NDVI	0.5218112	-0.4339306	-0.28600922	-0.11104681	-0.6672965
SO4	-0.3340839	-0.2932633	-0.75776632	-0.35985885	0.3141280

Ätran

Table 9.6-5. The principal component loadings of the variables for Ätran.

	PC1 (42.33 %)	**PC2 (25.18 %)**	**PC3 (20.27 %)**	**PC4 (8.641 %)**	**PC5 (3.577 %)**
Colour	0.5101473	-0.4106538	0.26516029	-0.3320272	0.6249489
Rainfall	-0.3940466	-0.4782323	0.41465457	0.6434562	0.1733405
Temperature	-0.5193924	-0.2105858	0.41282219	-0.6739144	-0.2475933
NDVI	-0.2754736	-0.5589792	-0.76353559	-0.1233549	0.1159893
SO4	-0.4886950	0.4958359	-0.06590033	-0.0796560	0.7103774

Päijänne

Table 9.6-6. The principal component loadings of the variables for Päijänne.

	PC1 (44.83 %)	**PC2 (20.05 %)**	**PC3 (16.23 %)**	**PC4 (12.29 %)**	**PC5 (6.596 %)**
Colour	0.5101473	-0.4106538	0.26516029	-0.3320272	0.6249489
Rainfall	-0.3940466	-0.4782323	0.41465457	0.6434562	0.1733405
Temperature	-0.5193924	-0.2105858	0.41282219	-0.6739144	-0.2475933

NDVI	-0.2754736	-0.5589792	-0.76353559	-0.1233549	0.1159893
SO4	-0.4886950	0.4958359	-0.06590033	-0.0796560	0.7103774

9.7 Appendix G RStudio scripts

RStudio Version 1.4.1106 was used in this thesis.

9.7.1 Packages

The RStudio packages used in this thesis are listed below.

dplyr

ncdf4

raster

sf

stringr

rgdal

mblm

readxl

timetools

rkt

nlme

ggplot2

ggfortify

writexl

9.7.2 RStudio scripts

Here the RStudio scripts used in this thesis are given. The script **read_nc.R** is where the .nc files for NDVI and acid deposition were read. Furthermore, there is one script for each catchment. Due to that some commands have been run directly in the Console, there is no guarantee that all code run is provided here.

read_nc.R

```
library(dplyr)
library(ncdf4)
library(raster)
library(sf)
library(stringr)
library(rgdal)
library(mblm)

#function for looping through one location in a given time period, returning a nx2 matrix
#with dates and NDVI value
NDVI_period <- function(start_year, stop_year, start_lat, stop_lat, start_long, stop_long){
  table <- data.frame(matrix(nrow = 0, ncol = 2))
  for (year in start_year:stop_year){
    if (year < 2012){
      setwd("C:/")
    } else{
      setwd("M:/")
    }
    path1 <- paste("NetCDF files summer", year, sep = "/")
    path1 <- paste(path1, "/", sep = "") #add a / in the end
    filenames <- list.files(path1, full.names=TRUE)
    print(filenames)
    for (i in 1:length(filenames)){
        ndvi <- mean_of_catchment(filenames[i], start_lat, stop_lat, start_long, stop_long)
        total_date <- filenames[i]
        total_date <- str_split(total_date, "c_gls_NDVI", simplify = TRUE)
        row <- cbind(total_date[2], ndvi)
        table <- rbind(table, row)
    }
  }
  return(table)
}

#Computes the mean of NDVI in a square defined by start and end longitude
#and latitude coordinates. Takes in path as argument to make this aspect easier.
mean_of_catchment <- function(path, start_lat, stop_lat, start_long, stop_long){
  #open the file
  ndvi <- nc_open(path)
  long_list <- ncvar_get(ndvi,"lon") #creates a vector with all longitudes
  lat_list <- ncvar_get(ndvi,"lat") #creates a vector with all latitudes

  lat_min <- which(lat_list<start_lat)[1] #finds which index to be the first smaller than start_lat
  lat_max <- which(lat_list<stop_lat)[1] #finds which index to be the first smaller than stop_lat

  long_min <- which(long_list>start_long)[1] #finds which index to be the first large enough
  long_max <- which(long_list>stop_long)[1] #finds which index to be the first above stop

  lat_count <- abs(lat_min-lat_max)+1 # How many lines must be used in the ncvar_get call
  long_count <- abs(long_min-long_max)+1 # How many lines must be used in the ncvar_get call
#  print(lat_count)
#  print(long_count)
  ndvi_vals <- ncvar_get(nc = ndvi,varid = "NDVI",start=c(long_min,lat_max,1),count=c(long_count,lat_count,1))
  #we must handle NDVI values higher than 0.92.
  number_NA1_ndvi <- sum(is.na(ndvi_vals))
  number_ndvi_vals <- length(ndvi_vals)
  print(ndvi_vals)
  ratio_originally_NA <- number_NA1_ndvi/number_ndvi_vals
  ndvi_vals[ndvi_vals > 0.92] <- NA #set the numbers higher than 0.92 to NA
  number_NA2_ndvi <- sum(is.na(ndvi_vals))
  ratio_NA <- number_NA2_ndvi/number_ndvi_vals
  print("after discarding values above 0.92")
  print(ndvi_vals)
#  print(ndvi_vals[,-3]) #dont know why I have [,-3] here.
  mean_ndvi <- data.frame(mean(ndvi_vals[,-3], na.rm = TRUE), ratio_originally_NA, ratio_NA) #compute mean and exclude the NA elements.
  colnames(mean_ndvi) <- c("NDVI", "ratio_original", "ratio")
  return(mean_ndvi)
}

#we use the function NDVI_period on the whole period for each catchment
Jordalsvatnet00_15 <- NDVI_period(2015,2015,60.42, 60.45, 5.32, 5.39)
NRV00_14 <- NDVI_period(1999,2014,61.08, 62.55, 10.08, 11.56)
PCharlotte99_15 <- NDVI_period(1999,2015, 55.748094, 55.762395, -6.431428, -6.405229)
Bracadale00_16 <- NDVI_period(2000, 2016, 57.358378, 57.382873, -6.421298, -6.398836)
Åtran00_13 <- NDVI_period(2000,2013,56.907, 57.472, 12.597, 13.311)
Paijanne00_15 <- NDVI_period(2000, 2015, 60.932124226, 63.456476636, 25.101002663, 27.174448549)

#handle NDVI matrix from different catchments
PCharlotte99_15 <- PCharlotte99_15[,-3:(-4)]
PCharlotte99_15$Date <- all_dates[1:nrow(PCharlotte99_15)]
write_xlsx(PCharlotte, "PCharlotte_NDVI.xlsx")

Bracadale00_16 <- Bracadale00_16[,-3:(-4)]
Bracadale_NDVI <- Bracadale00_16
Bracadale_NDVI$Date <- all_dates[10:(9 + nrow(Bracadale_NDVI))]
Bracadale_NDVI <- Bracadale_NDVI[,-1]
write_xlsx(Bracadale_NDVI, "Bracadale_NDVI.xlsx")

Karreberg_yearly_shape <- read.csv("Karreberg_yearly_shape.csv")
Karreberg_NDVI <- Karreberg_yearly_shape
Karreberg_NDVI$Date <- all_dates[1:nrow(Karreberg_yearly_shape)]
Karreberg_NDVI <- Karreberg_NDVI[,-1:(-2)]
write_xlsx(Karreberg_NDVI, "Karreberg_NDVI.xlsx")

Paijanne_NDVI <- Paijanne00_15
Paijanne_NDVI$Date <- all_dates[10:(9+nrow(Paijanne_NDVI))]
Paijanne_NDVI <- Paijanne_NDVI[,-1]
Paijanne_NDVI <- Paijanne_NDVI[,-2:(-3)]
write_xlsx(Paijanne_NDVI, "Paijanne_NDVI.xlsx")
```

```
boxplot(PCharlotte00_15$ratio_original, PCharlotte00_15$ratio, names = c("ratio NA","ratio NA + outside range"),
        main = "Port Charlotte")
boxplot(Bracadale01_16$ratio_original, Bracadale01_16$ratio, names = c("ratio NA","ratio NA + outside range"),
        main = "Bracadale")
boxplot(Paijanne01_15$ratio_original, Paijanne01_15$ratio, names = c("ratio NA","ratio NA + outside range"),
        main = "Päijänne")

#see a testplot of Port Charlotte through the whole 2016.
dates_2016 <- c("2016-01-01", "2016-01-11", "2016-01-21","2016-02-01", "2016-02-11", "2016-02-21",
  "2016-03-01", "2016-03-11", "2016-03-21","2016-04-01", "2016-04-11", "2016-04-21",
  "2016-05-01", "2016-05-11", "2016-05-21","2016-06-01", "2016-06-11", "2016-06-21",
  "2016-07-01", "2016-07-11", "2016-07-21","2016-08-01", "2016-08-11", "2016-08-21",
  "2016-09-01", "2016-09-11", "2016-09-21","2016-10-01", "2016-10-11", "2016-10-21",
  "2016-11-01", "2016-11-11", "2016-11-21","2016-12-01", "2016-12-11", "2016-12-21")
dates_2016 <- as.POSIXct(dates_2016)
plot(dates_2016, Paijanne01_15$NDVI, type = "l", lwd = 2.5, main = "Jordalsvatnet",
     ylab = "NDVI", xlab = "Year")

#take the mean of the month in each year in a catchment
annual_NDVI <- function(catchment_table, start_year, stop_year){
#transform NDVI elements to numeric
  catchment_table <- as.numeric(catchment_table[,2])
  year <- start_year:stop_year
  NDVI <- c()
  #make a list where the indexes are every 12th element
  index <- (seq(0,length(catchment_table),9))
  print(index)
  #define that we should loop length of catchment_table/12 times
  l <- length(index)-1
  for (i in 1:l){
    print(i)
    print(index[i]+1)
    print(index[i+1])
    mean_of_year <- mean(catchment_table[(index[i]+1):index[i+1]], na.rm = TRUE)
    print(catchment_table[(index[i]+1):index[i+1]])
    print(mean_of_year)
    NDVI <- append(NDVI, mean_of_year)
  }
  NDVI_matrix <- data.frame(year, NDVI)
  return(NDVI_matrix)
}

Jordalsvatnet_yearly <- annual_NDVI(Jordalsvatnet00_15, 2000, 2015)
NRV_yearly <- annual_NDVI(NRV00_14, 2000, 2014)
PCharlotte_yearly <- annual_NDVI(PCharlotte99_15, 1999, 2015)
Bracadale_yearly <- annual_NDVI(Bracadale00_16, 2000, 2016)
Åtran_yearly <- annual_NDVI(Åtran00_13, 2000, 2013)
Paijanne_yearly <- annual_NDVI(Paijanne00_15, 2000, 2015)

#Plot the monthly results
all_dates <- c("1999-06-01", "1999-06-11", "1999-06-21","1999-07-01", "1999-07-11", "1999-07-21","1999-08-01", "1999-08-11", "1999-08-21",
          "2000-06-01", "2000-06-11", "2000-06-21","2000-07-01", "2000-07-11", "2000-07-21","2000-08-01", "2000-08-11", "2000-08-21",
          "2001-06-01", "2001-06-11", "2001-06-21","2001-07-01", "2001-07-11", "2001-07-21","2001-08-01", "2001-08-11", "2001-08-21",
          "2002-06-01", "2002-06-11", "2002-06-21","2002-07-01", "2002-07-11", "2002-07-21","2002-08-01", "2002-08-11", "2002-08-21",
          "2003-06-01", "2003-06-11", "2003-06-21","2003-07-01", "2003-07-11", "2003-07-21","2003-08-01", "2003-08-11", "2003-08-21",
          "2004-06-01", "2004-06-11", "2004-06-21","2004-07-01", "2004-07-11", "2004-07-21","2004-08-01", "2004-08-11", "2004-08-21",
          "2005-06-01", "2005-06-11", "2005-06-21","2005-07-01", "2005-07-11", "2005-07-21","2005-08-01", "2005-08-11", "2005-08-21",
          "2006-06-01", "2006-06-11", "2006-06-21","2006-07-01", "2006-07-11", "2006-07-21","2006-08-01", "2006-08-11", "2006-08-21",
          "2007-06-01", "2007-06-11", "2007-06-21","2007-07-01", "2007-07-11", "2007-07-21","2007-08-01", "2007-08-11", "2007-08-21",
          "2008-06-01", "2008-06-11", "2008-06-21","2008-07-01", "2008-07-11", "2008-07-21","2008-08-01", "2008-08-11", "2008-08-21",
          "2009-06-01", "2009-06-11", "2009-06-21","2009-07-01", "2009-07-11", "2009-07-21","2009-08-01", "2009-08-11", "2009-08-21",
          "2010-06-01", "2010-06-11", "2010-06-21","2010-07-01", "2010-07-11", "2010-07-21","2010-08-01", "2010-08-11", "2010-08-21",
          "2011-06-01", "2011-06-11", "2011-06-21","2011-07-01", "2011-07-11", "2011-07-21","2011-08-01", "2011-08-11", "2011-08-21",
          "2012-06-01", "2012-06-11", "2012-06-21","2012-07-01", "2012-07-11", "2012-07-21","2012-08-01", "2012-08-11", "2012-08-21",
          "2013-06-01", "2013-06-11", "2013-06-21","2013-07-01", "2013-07-11", "2013-07-21","2013-08-01", "2013-08-11", "2013-08-21",
          "2014-06-01", "2014-06-11", "2014-06-21","2014-07-01", "2014-07-11", "2014-07-21","2014-08-01", "2014-08-11", "2014-08-21",
          "2015-06-01", "2015-06-11", "2015-06-21","2015-07-01", "2015-07-11", "2015-07-21","2015-08-01", "2015-08-11", "2015-08-21",
          "2016-06-01", "2016-06-11", "2016-06-21","2016-07-01", "2016-07-11", "2016-07-21","2016-08-01", "2016-08-11", "2016-08-21")
all_dates <- as.POSIXct(all_dates)

years <- c("1999-01-01","2000-01-01","2001-01-01","2002-01-01","2003-01-01",
          "2004-01-01","2005-01-01","2006-01-01","2007-01-01","2008-01-01",
          "2009-01-01","2010-01-01","2011-01-01","2012-01-01","2013-01-01",
          "2014-01-01","2015-01-01","2016-01-01")
years = as.POSIXct(years)

setwd("M:/NetCDF files summer/2016")
test <- nc_open("c_gls_NDVI_201606010000_GLOBE_PROBAV_V3.0.1.nc")


#function for reading in a shapefile and returning the ndvi values
#of the shapefile in a given period
#function for getting the mean NDVI values over a period for shapefiles. path is the
#path of the shp file


mean_of_shapefile <- function(path, start_year, stop_year){
  setwd("M:/Master thesis/NDVI data and R scripts")
  catchment_polygon <- st_read(path)
  table <- data.frame()
  for (year in start_year:stop_year){
    if (year < 2012){
      setwd("C:/")
    } else{
      setwd("M:/")
    }
    path1 <- paste("NetCDF files summer", year, sep = "/")
    filenames <- list.files(path1, full.names=TRUE)
    print(filenames[1])
    for (i in 1:9){
      ndvi_map <- raster(filenames[i], varname="NDVI")
```

```
      ndvi <- handle_shapefile(catchment_polygon, ndvi_map)
      total_date <- filenames[i]
      total_date <- str_split(total_date, "c_gls_NDVI", simplify = TRUE)
      row <- cbind(total_date[2], ndvi)
      print(total_date[2])
      table <- rbind(table, row)
    }
  }
#  colnames(table) = c("Date", "NDVI")
  return(table)
}

handle_shapefile <- function(catchment_polygon, ndvi_map){
  spdf <- as_Spatial(catchment_polygon$geometry,IDs=as.character(catchment_polygon$station_id)) #change of format in some way
  ndvi_vals <- extract(ndvi_map,spdf) #linking the catchment_polygon to the NDVI map
  number_NA1_ndvi <- sum(is.na(ndvi_vals[[1]]))
  number_ndvi_vals <- length(ndvi_vals[[1]])
  print(ndvi_vals)
  ratio_originally_NA <- number_NA1_ndvi/number_ndvi_vals
  ndvi_vals[ndvi_vals[[1]] > 0.92] <- NA #set the numbers higher than 0.92 to NA
  number_NA2_ndvi <- sum(is.na(ndvi_vals[[1]]))
  ratio_NA <- number_NA2_ndvi/number_ndvi_vals
  mean_ndvi <- data.frame(mean(ndvi_vals[[1]], na.rm = TRUE), ratio_originally_NA, ratio_NA) #compute mean and exclude the NA elements.
  colnames(mean_ndvi) <- c("NDVI", "ratio_original", "ratio")
  return(mean_ndvi)
}

#now we run the functions on the catchments that have shapefiles
Jordalsvatnet_shape <- "Jordal.shp"
Jordal_polygon <- st_read(Jordalsvatnet_shape)
Jordal_path_2000 <- "C:/NetCDF files summer/2000"
NRV_shape <- "NedbFeltF.shp"
Åtran_shape <- "buffert_export.shp"

Jordalsvatnet_table <- mean_of_shapefile(Jordalsvatnet_shape, 1999, 2015)
Jordalsvatnet_yearly_shape <- annual_NDVI(Jordalsvatnet_table, 1999, 2015)
write_xlsx(Jordalsvatnet_NDVI, "Jordalsvatnet_NDVI_shape.xlsx")
Jordalsvatnet_NDVI <- Jordalsvatnet_NDVI[,-2:(-3)]
Jordalsvatnet_NDVI$Date <- all_dates[1:nrow(Jordalsvatnet_NDVI)]
Jordalsvatnet_NDVI <- Jordalsvatnet_table[,-1]

NRV_table <- read.csv("NRV_NDVI_shape.csv")
NRV_table <- NRV_table[,-1:(-2)]
NRV_table$Date <- all_dates[1:nrow(NRV_table)]
NRV_table <- NRV_table[,-2:(-3)]
write_xlsx(NRV_table, "NRV_NDVI_shape.xlsx")

boxplot(Jordalsvatnet_table$ratio_original, Jordalsvatnet_table$ratio, names = c("ratio NA","ratio NA + outside range"),
        main = "Jordalsvatnet")

#Plot NDVI for the shapefile and compare it with the other
#----------- Jordalsvatnet shape ------------
#now we plot all observations of NDVI
plot(all_dates[1:153],Jordalsvatnet_table$NDVI, ylim = c(0.4,0.9),
     ylab = "NDVI", xlab = "Date", cex = 0.75, pch = 20)
#now we plot mean NDVI values for each year, as a function of year
plot(years[1:17], Jordalsvatnet_yearly_shape$NDVI, type = "l", ylim = c(0.4,0.9),
     ylab = "NDVI", xlab = "Year", pch = 20, lwd = 3, main = "Jordalsvatnet")
lines(years[1:16], Jordalsvatnet_yearly$NDVI, type = "l", ylim = c(0.4,0.9),
     ylab = "NDVI", xlab = "Year", pch = 20, lwd = 2, col = "blue")
legend(years[11],0.9, legend = c("shapefile","rectangle"), col=c("green","blue"),lty=1:1, cex=0.8, lwd = 2)
#fit a linear trend model of NDVI in Jordalsvatnet with Theil-Sen
Jordal_NDVI_poly1 <- mblm(NDVI~year, dataframe=Jordalsvatnet_yearly_shape,repeated = FALSE)
summary(Jordal_NDVI_poly1)
Jordal_NDVI_shape_predictions <- predict.lm(Jordal_NDVI_poly1)
lines(years[1:16], Jordal_NDVI_shape_predictions)
#fit a linear trend
Jordal_NDVI_poly1.2 <- lm(Jordalsvatnet_yearly_shape$NDVI~Jordalsvatnet_yearly_shape$year)
summary(Jordal_NDVI_poly1.2)

#----------- NRV shape ------------
NRV_table <- mean_of_shapefile(NRV_shape, 1999, 2014)
#save the values so that I dont lose them
write.csv(NRV_table,file = "NRV_yearly_shape.csv")
boxplot(NRV_table$ratio_original, NRV_table$ratio, names = c("ratio NA","ratio NA + outside range"),
        main = "Glomma")
NRV_yearly_shape <- annual_NDVI(NRV_table, 1999, 2014)
#now we plot all observations of NDVI
plot(all_dates[1:135],NRV_table$NDVI, type = "l", ylim = c(0.4,0.8),
     ylab = "NDVI", xlab = "Date", cex = 0.75, pch = 20)
#now we plot mean NDVI values for each year, as a function of year
plot(years[1:15], NRV_yearly_shape$NDVI, type = "l", ylim = c(0.4,0.7),
     ylab = "NDVI", xlab = "Year", pch = 20, lwd = 2)
lines(years[1:15], NRV_yearly$NDVI, type = "l", ylim = c(0.4,0.7),
      ylab = "NDVI", xlab = "Year", pch = 20, lwd = 2, col = "blue")
legend(years[10],0.7, legend = c("shapefile","rectangle"), col=c("green","blue"),lty=1:1, cex=0.8, lwd = 2)
#fit a Theil-Sen estimator of NDVI against years in NRV
NRV_NDVI_poly1 <- mblm(NDVI~year, dataframe = NRV_yearly_shape)
summary(NRV_NDVI_poly1)
predicted_NDVI_NRV <- predict.lm(NRV_NDVI_poly1)
lines(years[1:15], predicted_NDVI_NRV, type = "l", ylim = c(0.4,0.7),
      ylab = "NDVI", xlab = "Year", pch = 20, lwd = 2, col = "red")
#fit a linear trend model of NDVI in NRV
NRV_NDVI_poly1.2 <- lm(NRV_yearly_shape$NDVI~years[1:15])
summary(NRV_NDVI_poly1.2)

#----------- Åtran shape ------------
Åtran_table <- mean_of_shapefile(Åtran_shape, 1999, 2013)
Åtran_yearly_shape <- annual_NDVI(Åtran_table, 1999, 2013)
write.csv(Åtran_table,file = "Karreberg_yearly_shape.csv")
boxplot(Åtran_table$ratio_original, Åtran_table$ratio, names = c("original ratio","ratio"),
```

```
        main = "Kärreberg")
#now we plot all observations of NDVI
plot(all_dates[1:126], Åtran_table$NDVI, type = "l", ylim = c(0.45,0.85),
     ylab = "NDVI", xlab = "Date", cex = 0.75, pch = 20)
#now we plot mean NDVI values for each year, as a function of year
plot(years[1:14], Åtran_yearly_shape$NDVI, type = "l", ylim = c(0.45,0.85),
     ylab = "NDVI", xlab = "Year", pch = 20, lwd = 2, main = "Kärreberg")
lines(years[1:14], Åtran_yearly$NDVI, type = "l", ylim = c(0.4,0.9),
      ylab = "NDVI", xlab = "Year", pch = 20, lwd = 2, col = "blue")
#fit a Theil-Sen estimator
Åtran_NDVI_poly1 <- mblm(NDVI~year, dataframe = Åtran_yearly_shape)
summary(Åtran_NDVI_poly1)
Åtran_NDVI_predictions <- predict.lm(Åtran_NDVI_poly1)
lines(years[1:14], Åtran_NDVI_predictions, type = "l", ylim = c(0.4,0.7),
      ylab = "NDVI", xlab = "Year", pch = 20, lwd = 2, col = "red")

#fit a linear trend model of NDVI in NRV
Åtran_NDVI_poly1.1 <- lm(Åtran_yearly_shape$NDVI~years[1:15])
summary(Åtran_NDVI_poly1.1)

#import .nc files with acid deposition data
setwd("M:/Master thesis/NDVI data and R scripts") #set directory to current
path2 <- "Deposition data/2015/EMEP01_L20EC_rv4_33_year.2015met_2015emis_rep2019.nc"
dep_data <- nc_open(path2)
path3 <- "Deposition data/EMEP01_L20EC_rv4_33_year.2015met_2015emis_rep2019.nc"
dep_data3 <- nc_open(path3)
DDEP_SO4_year_2015 <- ncvar_get(nc = dep_data3,varid = "DDEP_SOX_m2Grid",start=c(1,1,1),count=c(1,1,1))
WDEP_SO4_year_2015 <- ncvar_get(nc = dep_data3,varid = "WDEP_SOX",start=c(1,1,1),count=c(1,1,1))

NO3_year_2015 <- ncvar_get(nc = dep_data3,varid = "SURF_ug_NO3_C",start=c(1,1,1),count=c(1,1,1))

DDEP_SO4_month_2015 <- ncvar_get(nc = dep_data,varid = "DDEP_SOX_m2Grid",start=c(1,1,1),count=c(1,1,12))
WDEP_SO4_month_2015 <- ncvar_get(nc = dep_data,varid = "WDEP_SOX",start=c(1,1,1),count=c(1,1,12))

#function for extracting mean SO4 value from a given path/file, on given location
#defined by starting and stopping latitude and longitude coordinates.
get_SO4 <- function(path, start_lat, stop_lat, start_long, stop_long){
  #open the file
  SO4 <- nc_open(path)
  long_list <- ncvar_get(SO4,"lon") #creates a vector with all longitudes
  lat_list <- ncvar_get(SO4,"lat") #creates a vector with all latitudes

  lat_min <- which(lat_list>start_lat)[1] #finds which index to be the first smaller than start_lat
  lat_max <- which(lat_list>stop_lat)[1] #finds which index to be the first smaller than stop_lat

  long_min <- which(long_list>start_long)[1] #finds which index to be the first large enough
  long_max <- which(long_list>stop_long)[1] #finds which index to be the first above stop

  lat_count <- abs(lat_min-lat_max)+1 # How many lines must be used in the ncvar_get call
  long_count <- abs(long_min-long_max)+1 # How many lines must be used in the ncvar_get call

  SO4_DDEP_vals <- ncvar_get(nc = SO4,varid = "DDEP_SOX_m2Grid",start=c(long_min,lat_max,1),count=c(long_count,lat_count,1))
  SO4_WDEP_vals <- ncvar_get(nc = SO4,varid = "WDEP_SOX",start=c(long_min,lat_max,1),count=c(long_count,lat_count,1))

  SO4_DDEP_mean <- mean(SO4_DDEP_vals, na.rm = TRUE) #compute mean and exclude the NA elements.
  SO4_WDEP_mean <- mean(SO4_WDEP_vals, na.rm = TRUE) #compute mean and exclude the NA elements.
  SO4_total <- SO4_DDEP_mean + SO4_WDEP_mean

  return(SO4_total)
}

get_NO3 <- function(path, start_lat, stop_lat, start_long, stop_long){
  NO3 <- nc_open(path)
  long_list <- ncvar_get(NO3,"lon") #creates a vector with all longitudes
  lat_list <- ncvar_get(NO3,"lat") #creates a vector with all latitudes

  lat_min <- which(lat_list>start_lat)[1] #finds which index to be the first smaller than start_lat
  lat_max <- which(lat_list>stop_lat)[1] #finds which index to be the first smaller than stop_lat

  long_min <- which(long_list>start_long)[1] #finds which index to be the first large enough
  long_max <- which(long_list>stop_long)[1] #finds which index to be the first above stop

  lat_count <- abs(lat_min-lat_max)+1 # How many lines must be used in the ncvar_get call
  long_count <- abs(long_min-long_max)+1 # How many lines must be used in the ncvar_get call
  NO3_DDEP_vals <- ncvar_get(nc = NO3,varid = "DDEP_OXN_m2Grid",start=c(long_min,lat_max,1),count=c(long_count,lat_count,1))
  NO3_WDEP_vals <- ncvar_get(nc = NO3,varid = "WDEP_OXN",start=c(long_min,lat_max,1),count=c(long_count,lat_count,1))

  NO3_DDEP_mean <- mean(NO3_DDEP_vals, na.rm = TRUE) #compute mean and exclude the NA elements.
  NO3_WDEP_mean <- mean(NO3_WDEP_vals, na.rm = TRUE) #compute mean and exclude the NA elements.
  return(NO3_DDEP_mean + NO3_WDEP_mean)
}

SO4_2015 <- get_SO4(path2, 60.42, 60.45, 5.32, 5.39)
NO3_2015 <- get_NO3(path2, 60.42, 60.45, 5.32, 5.39)

#get a table for the SO4 and NO3 deposition for each year in a given period for
#given coordinates
acid_period <- function(start_year, stop_year, start_lat, stop_lat, start_long, stop_long){
  acid_table <- data.frame()
  for (year in start_year:stop_year){
    setwd("M:/Master thesis/NDVI data and R scripts/Deposition data")
    path1 <- paste(year, sep = "/") #define a path for getting into the correct year folder
    filenames <- list.files(path1, full.names=TRUE)
    path2 <- paste(year, filenames, sep = "/") #define the path to the file we want
    SO4_year <- get_SO4(filenames, start_lat, stop_lat, start_long, stop_long)
    NO3_year <- get_NO3(filenames, start_lat, stop_lat, start_long, stop_long)
    row <- c(year, SO4_year, NO3_year)
    acid_table <- rbind(acid_table, row)
  }
  colnames(acid_table) <- c("Year", "SO4", "NO3")
  return(acid_table)
```

```
}

Jordalsvatnet_acid <- acid_period(2000, 2015, 60.42, 60.45, 5.32, 5.39)
NRV_acid <- acid_period(2000,2014,61.08, 62.55, 10.08, 11.56)
PCharlotte_acid <- acid_period(2000,2015, 55.748094, 55.762395, -6.431428, -6.405229)
Bracadale_acid <- acid_period(2001, 2016, 57.358378, 57.382873, -6.421298, -6.398836)
Åtran_acid <- acid_period(2000,2013,56.907, 57.472, 12.597, 13.311)
Bolmen_acid <- acid_period(2000,2007, 56.457, 57.635, 13.427, 14.634)
Paijanne_acid <- acid_period(2001,2015, 60.932124226, 63.456476636, 25.101002663, 27.174448549)

write_xlsx(PCharlotte_acid, "PCharlotte_Year_SO4_NO3.xlsx")
write_xlsx(Bracadale_acid, "Bracadale_Year_SO4_NO3.xlsx")
write_xlsx(Paijanne_acid, "Paijanne_Year_SO4_NO3.xlsx")


#--------------Jordalsvatnet-----------
#plot the change in acid deposition
plot(Jordalsvatnet_acid$Year, Jordalsvatnet_acid$SO4, type = "l", col = "red", ylim = c(0,1000),
    xlab = "Year", ylab = "Concentration acid dep. (mg (S/N)/m^2)", lwd = 2.5)
par(new = T)
plot(Jordalsvatnet_acid$Year, Jordalsvatnet_acid$NO3, type = "l", col = "green", ylim = c(0,1000),
    xlab = "Year", ylab = "Concentration acid dep. (mg (S/N)/m^2)", lwd = 2.5)
legend(2000, 300, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a model of acid deposition against year
Jordalsvatnet_sulfate_year_poly1 <- lm(Jordalsvatnet_acid$SO4~Jordalsvatnet_acid$Year)
summary(Jordalsvatnet_sulfate_year_poly1)

Jordalsvatnet_nitrate_year_poly1 <- lm(Jordalsvatnet_acid$NO3~Jordalsvatnet_acid$Year)
summary(Jordalsvatnet_nitrate_year_poly1)

predictions_sulfate <- predict.lm(Jordalsvatnet_sulfate_year_poly1)
lines(Jordalsvatnet_acid$Year, predictions_sulfate, lwd = 3, col = "firebrick")
predictions_nitrate <- predict.lm(Jordalsvatnet_nitrate_year_poly1)
lines(Jordalsvatnet_acid$Year, predictions_nitrate, lwd = 3, col = "forestgreen")

#Theil-Sen estimator
Jordalsvatnet_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Jordalsvatnet_acid, repeated = FALSE)
summary(Jordalsvatnet_sulfate_year_poly1_TS)

Jordalsvatnet_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Jordalsvatnet_acid, repeated = FALSE)
summary(Jordalsvatnet_nitrate_year_poly1_TS)

plot(Jordalsvatnet_acid$Year, Jordalsvatnet_acid$SO4, type = "l", col = "red", ylim = c(0,1000),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Jordalsvatnet")
par(new = T)
plot(Jordalsvatnet_acid$Year, Jordalsvatnet_acid$NO3, type = "l", col = "green", ylim = c(0,1000),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Jordalsvatnet")
legend(2000, 300, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#make predictions with Theil-Sen for sulfate and nitrate
predictions_sulfate_TS <- predict.lm(Jordalsvatnet_sulfate_year_poly1_TS)
lines(Jordalsvatnet_acid$Year, predictions_sulfate_TS, lwd = 3, col = "firebrick")
predictions_nitrate_TS <- predict.lm(Jordalsvatnet_nitrate_year_poly1_TS)
lines(Jordalsvatnet_acid$Year, predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#------------NRV-----------
#plot the change in acid deposition
plot(NRV_acid$Year, NRV_acid$SO4, type = "l", col = "red", ylim = c(0,200),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "NRV")
par(new = T)
plot(NRV_acid$Year, NRV_acid$NO3, type = "l", col = "green", ylim = c(0,200),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "NRV")
legend(2000, 50, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a model of acid deposition against year
#there might be an outlier in 2014
boxplot(NRV_acid$SO4) #visualize the distribution of the observations
library(outliers)
grubbs.test(NRV_acid$SO4) #p-value=0.08777, means that it is not an outlier
#models with and without the 2014 observation is fitted
NRV_sulfate_year_poly1 <- lm(NRV_acid$SO4~NRV_acid$Year)
summary(NRV_sulfate_year_poly1)
NRV_sulfate_year_poly1 <- lm(NRV_acid$SO4[1:14]~NRV_acid$Year[1:14])
summary(NRV_sulfate_year_poly1)

NRV_nitrate_year_poly1 <- lm(NRV_acid$NO3~NRV_acid$Year)
summary(NRV_nitrate_year_poly1)
#make predictions for nitrate with the linear model and plot this
NRV_predictions_nitrate <- predict.lm(NRV_nitrate_year_poly1)
lines(NRV_acid$Year, NRV_predictions_nitrate, lwd = 3, col = "forestgreen")

#fit Theil-sen model
library(mblm)
NRV_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = NRV_acid, repeated = FALSE)
summary(NRV_sulfate_year_poly1_TS)

NRV_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = NRV_acid, repeated = FALSE)
summary(NRV_nitrate_year_poly1_TS)

plot(NRV_acid$Year, NRV_acid$SO4, type = "l", col = "red", ylim = c(0,200),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "NRV")
par(new = T)
plot(NRV_acid$Year, NRV_acid$NO3, type = "l", col = "green", ylim = c(0,200),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "NRV")
legend(2000, 50, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#make predictions with Theil-Sen for sulfate and nitrate
NRV_predictions_sulfate_TS <- predict.lm(NRV_sulfate_year_poly1_TS)
lines(NRV_acid$Year, NRV_predictions_sulfate_TS, lwd = 3, col = "firebrick")
NRV_predictions_nitrate_TS <- predict.lm(NRV_nitrate_year_poly1_TS)
```

```
lines(NRV_acid$Year, NRV_predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#--------------Port Charlotte-----------
#plot the change in acid deposition
plot(PCharlotte_acid$Year, PCharlotte_acid$SO4, type = "l", col = "red", ylim = c(0,500),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Port Charlotte")
par(new = T)
plot(PCharlotte_acid$Year, PCharlotte_acid$NO3, type = "l", col = "green", ylim = c(0,500),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Port Charlotte")
legend(2000, 100, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a model of acid deposition against year
PCharlotte_sulfate_year_poly1 <- lm(PCharlotte_acid$SO4~PCharlotte_acid$Year)
summary(PCharlotte_sulfate_year_poly1)

PCharlotte_nitrate_year_poly1 <- lm(PCharlotte_acid$NO3~PCharlotte_acid$Year)
summary(PCharlotte_nitrate_year_poly1)
#plot the line of the linear fitted model
PCharlotte_predictions_sulfate <- predict.lm(PCharlotte_sulfate_year_poly1)
lines(PCharlotte_acid$Year, PCharlotte_predictions_sulfate, lwd = 3, col = "firebrick")
PCharlotte_predictions_nitrate <- predict.lm(PCharlotte_nitrate_year_poly1)
lines(PCharlotte_acid$Year, PCharlotte_predictions_nitrate, lwd = 3, col = "forestgreen")

#now I want to fit a Theil-Sen estimator of acid deposition against year
PCharlotte_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = PCharlotte_acid, repeated = FALSE)
summary(PCharlotte_sulfate_year_poly1_TS)

PCharlotte_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = PCharlotte_acid, repeated = FALSE)
summary(PCharlotte_nitrate_year_poly1_TS)

#plot Theil-Sen
plot(PCharlotte_acid$Year, PCharlotte_acid$SO4, type = "l", col = "red", ylim = c(0,500),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Port Charlotte")
par(new = T)
plot(PCharlotte_acid$Year, PCharlotte_acid$NO3, type = "l", col = "green", ylim = c(0,500),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Port Charlotte")
legend(2000, 100, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

PCharlotte_predictions_sulfate_TS <- predict.lm(PCharlotte_sulfate_year_poly1_TS)
lines(PCharlotte_acid$Year, PCharlotte_predictions_sulfate_TS, lwd = 3, col = "firebrick")
PCharlotte_predictions_nitrate_TS <- predict.lm(PCharlotte_nitrate_year_poly1_TS)
lines(PCharlotte_acid$Year, PCharlotte_predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#--------------Bracadale-----------
#plot the change in acid deposition
plot(Bracadale_acid$Year, Bracadale_acid$SO4, type = "l", col = "red", ylim = c(0,400),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Bracadale")
par(new = T)
plot(Bracadale_acid$Year, Bracadale_acid$NO3, type = "l", col = "green", ylim = c(0,400),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Bracadale")
legend(2001, 125, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a model of acid deposition against year
Bracadale_sulfate_year_poly1 <- lm(Bracadale_acid$SO4~Bracadale_acid$Year)
summary(Bracadale_sulfate_year_poly1)

Bracadale_nitrate_year_poly1 <- lm(Bracadale_acid$NO3~Bracadale_acid$Year)
summary(Bracadale_nitrate_year_poly1)

Bracadale_predictions_sulfate <- predict.lm(Bracadale_sulfate_year_poly1)
lines(Bracadale_acid$Year, Bracadale_predictions_sulfate, lwd = 3, col = "firebrick")
Bracadale_predictions_nitrate <- predict.lm(Bracadale_nitrate_year_poly1)
lines(Bracadale_acid$Year, Bracadale_predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a Theil-Sen estimator
plot(Bracadale_acid$Year, Bracadale_acid$SO4, type = "l", col = "red", ylim = c(0,400),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Bracadale")
par(new = T)
plot(Bracadale_acid$Year, Bracadale_acid$NO3, type = "l", col = "green", ylim = c(0,400),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Bracadale")
legend(2001, 125, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a Theil-Sen estimator
Bracadale_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Bracadale_acid, repeated = FALSE)
summary(Bracadale_sulfate_year_poly1_TS)

Bracadale_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Bracadale_acid, repeated = FALSE)
summary(Bracadale_nitrate_year_poly1_TS)

Bracadale_predictions_sulfate_TS <- predict.lm(Bracadale_sulfate_year_poly1_TS)
lines(Bracadale_acid$Year, Bracadale_predictions_sulfate_TS, lwd = 3, col = "firebrick")
Bracadale_predictions_nitrate_TS <- predict.lm(Bracadale_nitrate_year_poly1_TS)
lines(Bracadale_acid$Year, Bracadale_predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#--------------Åtran-----------
#plot the change in acid deposition
plot(Åtran_acid$Year, Åtran_acid$SO4, type = "l", col = "red", ylim = c(0,800),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Kärreberg")
par(new = T)
plot(Åtran_acid$Year, Åtran_acid$NO3, type = "l", col = "green", ylim = c(0,800),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Kärreberg")
legend(2000, 200, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a model of acid deposition against year
Åtran_sulfate_year_poly1 <- lm(Åtran_acid$SO4~Åtran_acid$Year)
summary(Åtran_sulfate_year_poly1)

Åtran_nitrate_year_poly1 <- lm(Åtran_acid$NO3~Åtran_acid$Year)
summary(Åtran_nitrate_year_poly1)

Åtran_predictions_sulfate <- predict.lm(Åtran_sulfate_year_poly1)
```

```
lines(Åtran_acid$Year, Åtran_predictions_sulfate, lwd = 3, col = "firebrick")
Åtran_predictions_nitrate <- predict.lm(Åtran_nitrate_year_poly1)
lines(Åtran_acid$Year, Åtran_predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a Theil-Sen estimator
plot(Åtran_acid$Year, Åtran_acid$SO4, type = "l", col = "red", ylim = c(0,800),
     xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Kärreberg")
par(new = T)
plot(Åtran_acid$Year, Åtran_acid$NO3, type = "l", col = "green", ylim = c(0,800),
     xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Kärreberg")
legend(2000, 200, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a Theil-Sen estimator
Åtran_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Åtran_acid, repeated = FALSE)
summary(Åtran_sulfate_year_poly1_TS)

Åtran_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Åtran_acid, repeated = FALSE)
summary(Åtran_nitrate_year_poly1_TS)

Åtran_predictions_sulfate_TS <- predict.lm(Åtran_sulfate_year_poly1_TS)
lines(Åtran_acid$Year, Åtran_predictions_sulfate_TS, lwd = 3, col = "firebrick")
Åtran_predictions_nitrate_TS <- predict.lm(Åtran_nitrate_year_poly1_TS)
lines(Åtran_acid$Year, Åtran_predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#--------------Paijanne-----------
#plot the change in acid deposition
plot(Paijanne_acid$Year, Paijanne_acid$SO4, type = "l", col = "red", ylim = c(0,400),
     xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Päijänne")
par(new = T)
plot(Paijanne_acid$Year, Paijanne_acid$NO3, type = "l", col = "green", ylim = c(0,400),
     xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Päijänne")
legend(2001, 100, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a model of acid deposition against year
Paijanne_sulfate_year_poly1 <- lm(Paijanne_acid$SO4~Paijanne_acid$Year)
summary(Paijanne_sulfate_year_poly1)

Paijanne_nitrate_year_poly1 <- lm(Paijanne_acid$NO3~Paijanne_acid$Year)
summary(Paijanne_nitrate_year_poly1)

Paijanne_predictions_sulfate <- predict.lm(Paijanne_sulfate_year_poly1)
lines(Paijanne_acid$Year, Paijanne_predictions_sulfate, lwd = 3, col = "firebrick")
Paijanne_predictions_nitrate <- predict.lm(Paijanne_nitrate_year_poly1)
lines(Paijanne_acid$Year, Paijanne_predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a Theil-Sen estimator
plot(Paijanne_acid$Year, Paijanne_acid$SO4, type = "l", col = "red", ylim = c(0,400),
     xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Päijänne")
par(new = T)
plot(Paijanne_acid$Year, Paijanne_acid$NO3, type = "l", col = "green", ylim = c(0,400),
     xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Päijänne")
legend(2001, 100, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#now I want to fit a Theil-Sen estimator
Paijanne_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Paijanne_acid, repeated = FALSE)
summary(Paijanne_sulfate_year_poly1_TS)

Paijanne_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Paijanne_acid, repeated = FALSE)
summary(Paijanne_nitrate_year_poly1_TS)

Paijanne_predictions_sulfate_TS <- predict.lm(Paijanne_sulfate_year_poly1_TS)
lines(Paijanne_acid$Year, Paijanne_predictions_sulfate_TS, lwd = 3, col = "firebrick")
Paijanne_predictions_nitrate_TS <- predict.lm(Paijanne_nitrate_year_poly1_TS)
lines(Paijanne_acid$Year, Paijanne_predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#-------------use shapefiles to define coordinates for acid deposition data-----------------

mean_SO4_of_shapefile <- function(path, start_year, stop_year){
  setwd("M:/Master thesis/NDVI data and R scripts")
  catchment_polygon <- st_read(path)
  table <- data.frame()
  for (year in start_year:stop_year) {
    path1 <- paste("Deposition data", year, sep = "/")
    filenames <- list.files(path1, full.names=TRUE)
    print(filenames[1])
    SO4_wet_map <- raster(filenames[1], varname="WDEP_SOX")
    SO4_wet <- handle_shapefile(catchment_polygon, SO4_wet_map)
    SO4_dry_map <- raster(filenames[1], varname="DDEP_SOX_m2Grid")
    SO4_dry <- handle_shapefile(catchment_polygon, SO4_dry_map)
    row <- c(year, SO4_wet+SO4_dry)
    table <- rbind(table, row)
  }
  colnames(table) = c("Year", "SO4")
  return(table)
}

mean_NO3_of_shapefile <- function(path, start_year, stop_year){
  setwd("M:/Master thesis/NDVI data and R scripts")
  catchment_polygon <- st_read(path)
  table <- data.frame()
  for (year in start_year:stop_year) {
    path1 <- paste("Deposition data", year, sep = "/")
    filenames <- list.files(path1, full.names=TRUE)
    print(filenames[1])
    NO3_wet_map <- raster(filenames[1], varname="WDEP_OXN")
    NO3_wet <- handle_shapefile(catchment_polygon, NO3_wet_map)
    NO3_dry_map <- raster(filenames[1], varname="DDEP_OXN_m2Grid")
    NO3_dry <- handle_shapefile(catchment_polygon, NO3_dry_map)
    row <- c(year, NO3_wet+NO3_dry)
    table <- rbind(table, row)
  }
```

```
  colnames(table) = c("Year", "NO3")
  return(table)
}

handle_shapefile <- function(catchment_polygon, ndvi_map){
  spdf <- as_Spatial(catchment_polygon$geometry,IDs=as.character(catchment_polygon$station_id)) #change of format in some way
  ndvi_vals <- extract(ndvi_map,spdf) #linking the catchment_polygon to the NDVI map
  print(ndvi_vals)
  ndvi <- mean(ndvi_vals[[1]], na.rm = TRUE)
  return(ndvi)
}

setwd("M:/Master thesis/NDVI data and R scripts") #set directory to current
Jordalsvatnet_shape <- "Jordal.shp"
Jordal_polygon <- st_read(Jordalsvatnet_shape)
Jordal_path_2000 <- "C:/NetCDF files summer/2000"
NRV_shape <- "NedbFeltF.shp"
Åtran_shape <- "buffert_export.shp"

Jordalsvatnet_shape_SO4 <- mean_SO4_of_shapefile(Jordalsvatnet_shape, 2000, 2015)
Jordalsvatnet_shape_NO3 <- mean_NO3_of_shapefile(Jordalsvatnet_shape, 2000, 2015)
cor(Jordalsvatnet_shape_SO4$SO4, Jordalsvatnet_shape_NO3$NO3)
Jordalsvatnet_shape_SO4$NO3 <- Jordalsvatnet_shape_NO3$NO3
write_xlsx(Jordalsvatnet_shape_SO4, "Jordalsvatnet_Year_SO4_NO3.xlsx")

NRV_shape_SO4 <- mean_SO4_of_shapefile(NRV_shape, 2000, 2014)
NRV_shape_NO3 <- mean_NO3_of_shapefile(NRV_shape, 2000, 2014)
NRV_shape_SO4$NO3 <- NRV_shape_NO3$NO3
write_xlsx(NRV_shape_SO4, "NRV_Year_SO4_NO3.xlsx")

Karreberg_shape_SO4 <- mean_SO4_of_shapefile(Åtran_shape, 2000, 2013)
Karreberg_shape_NO3 <- mean_NO3_of_shapefile(Åtran_shape, 2000, 2013)
Karreberg_shape_SO4$NO3 <- Karreberg_shape_NO3$NO3
write_xlsx(Karreberg_shape_SO4, "Karreberg_Year_SO4_NO3.xlsx")

#fit Theil-Sen model
Jordalsvatnet_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Jordalsvatnet_shape_SO4, repeated = FALSE)
summary(Jordalsvatnet_sulfate_year_poly1_TS)

Jordalsvatnet_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Jordalsvatnet_shape_NO3, repeated = FALSE)
summary(Jordalsvatnet_nitrate_year_poly1_TS)

plot(years[1:17], Jordalsvatnet_yearly_shape, type = "l", col = "red", ylim = c(0,1200),
     xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Jordalsvatnet")
par(new = T)
plot(Jordalsvatnet_acid$Year, Jordalsvatnet_acid$NO3, type = "l", col = "green", ylim = c(0,1000),
     xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Jordalsvatnet")
legend(2000, 300, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)

#fit a linear model
Jordalsvatnet_sulfate_year_poly1 <- lm(Jordalsvatnet_shape_SO4$SO4~Jordalsvatnet_acid$Year)
summary(Jordalsvatnet_sulfate_year_poly1)

Jordalsvatnet_nitrate_year_poly1 <- lm(Jordalsvatnet_acid$NO3~Jordalsvatnet_acid$Year)
summary(Jordalsvatnet_nitrate_year_poly1)

predictions_sulfate <- predict.lm(Jordalsvatnet_sulfate_year_poly1)
lines(Jordalsvatnet_acid$Year, predictions_sulfate, lwd = 3, col = "firebrick")
predictions_nitrate <- predict.lm(Jordalsvatnet_nitrate_year_poly1)
lines(Jordalsvatnet_acid$Year, predictions_nitrate, lwd = 3, col = "forestgreen")

#now I want to fit a model of acid deposition affecting color. Needs variables from other R script
sulfate_color_Jordal <- lm(water_table_00_15$`Mean color`~Jordalsvatnet_acid$SO4)
summary(sulfate_color_Jordal)

nitrate_color_Jordal <- lm(water_table_00_15$`Mean color`~Jordalsvatnet_acid$NO3)
summary(nitrate_color_Jordal)

acid_color_Jordal <- lm(water_table_00_15$`Mean color`~Jordalsvatnet_acid$SO4 + Jordalsvatnet_acid$NO3)
summary(acid_color_Jordal)

#now we want to plot color against sulfate, nitrate, and use the fitted models to predict color
plot(Jordalsvatnet_acid$SO4, water_table_00_15$`Mean color`)

sulfate_color_predictions <- predict.lm(sulfate_color_Jordal)
lines(Jordalsvatnet_acid$SO4, sulfate_color_predictions)

lines(water_table_00_15$Year, sulfate_color_predictions)
nitrate_color_predictions <- predict.lm(nitrate_color_Jordal)
lines(water_table_00_15$Year, nitrate_color_predictions)
acid_color_predictions <- predict.lm(acid_color_Jordal)
lines(water_table_00_15$Year, acid_color_predictions)
```

Jordalsvatnet.R

```
#Analyzing data from Jordalsvatnet ----------------

library("readxl")
library("timetools")
library(rkt)
library(nlme)
library(ggplot2)
library(ggfortify)
library(writexl)

#read in the data
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "1. B Jordalsvatnet")

#define years list in order to use in plots and models
years <- c("2000-01-01","2001-01-01","2002-01-01","2003-01-01",
           "2004-01-01","2005-01-01","2006-01-01","2007-01-01","2008-01-01",
           "2009-01-01","2010-01-01","2011-01-01","2012-01-01","2013-01-01",
           "2014-01-01","2015-01-01","2016-01-01")
years = as.POSIXct(years)

#handling the data for date and color. Make a model for color vs date
water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
water_data <- na.omit(water_data) #get rid of the NA values
water_data <- water_data[7:nrow(water_data),] #in order to discard the year 1999
colnames(water_data) <- c("Date","Color")
water_data$Color <- as.numeric(water_data$Color) #make color data numeric
water_data <- water_data[order(water_data$Date),] #sort the data on date

#fit a linear Theil-Sen model of color in Jordalsvatnet
Jordalsvatnet_color_poly1_TS <- mblm(Color~Num_date, dataframe = water_data, repeated = FALSE)
summary(Jordalsvatnet_color_poly1_TS)
#predict color for Jordalsvatnet with Theil-Sen model
Jordal_color_predictions_TS <- predict.lm(object = Jordalsvatnet_color_poly1_TS)
plot(water_data$Date, water_data$Color, xlab = "Date", ylab = "Colour (mg Pt/l)",
     cex = 0.75, pch = 20, main = "Jordalsvatnet")
lines(water_data$Date, Jordal_color_predictions_TS, lwd = 3, col = "red")

#fit polynomial models of degree 1 on color vs days after January 1 2000
Jordalsvatnet_color_poly1 <- lm(Color~Date, data = water_data)
summary(Jordalsvatnet_color_poly1)

Jordal_color_predictions <- predict.lm(object = Jordalsvatnet_color_poly1)
#make scatter plot and plot of model
plot(water_data$Date, water_data$Color, xlab = "Date", ylab = "Colour (mg Pt/l)",
     cex = 0.75, pch = 20, main = "Jordalsvatnet")
lines(water_data$Date, Jordal_color_predictions, col = "red", lwd = 3)
#find slope of linear fitted line
days <- 5522
slope <- (predictions[length(predictions)]-predictions[1])/days
seconds_in_year <- 3600*24*365.25

#function for computing the mean color in each year
annual_color <- function(table, start_year, stop_year){
  color_mean <- c()
  year_list <- table$Date
  year_list <- POSIXst(year_list, "year")
  year_list <- year_list@subtime
  for (year in start_year:stop_year){
    color_mean <- append(color_mean, mean(table$Color[year_list == year]))
  }
  new_water_table <- data.frame(start_year:stop_year, color_mean)
  colnames(new_water_table) <- c("Year", "Mean color")
  return(new_water_table)
}

#make tables with mean annual color in order to plot mean color vs prec and temp
water_table_00_15 <- annual_color(water_data, 2000, 2015)

#read in rainfall data from Norsk Klimaservicesenter

rainfall <- read_excel("Jordalsvatnet_rainfall.xlsx")
rainfall <- na.omit(rainfall)
rainfall$`Nedbør (mnd)` <- as.numeric(rainfall$`Nedbør (mnd)`) #make rainfall numeric in order to calculate
#want to rewrite the dates to POSIXct format
x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=192), "%Y-%m-%d")
rainfall$Months <- as.POSIXct(months)
#in order to fit a Theil-Sen estimator
rainfall$months_index <- c(1:nrow(rainfall))

plot(rainfall$Months, rainfall$`Nedbør (mnd)`, xlab = "date (monthly)",
     ylab = "rainfall (mm)", type = "h", main = "Bergen (Jordalsvatnet)", col = "blue")
#fit a model for rainfall against days
Jordal_prec_months_poly1 <- lm(`Nedbør (mnd)`~Months, data = rainfall)
summary(Jordal_prec_days_poly1)
#fit a Theil-Sen model for rainfall against years
Jordal_prec_months_TS <- mblm(`Nedbør (mnd)`~months_index, dataframe = rainfall)
summary(Jordal_prec_months_TS)

#define years list in order to plot season rainfall data for each year later
years <- c("2000-01-01","2001-01-01","2002-01-01","2003-01-01",
           "2004-01-01","2005-01-01","2006-01-01","2007-01-01","2008-01-01",
           "2009-01-01","2010-01-01","2011-01-01","2012-01-01","2013-01-01",
           "2014-01-01","2015-01-01","2016-01-01")
years = as.POSIXct(years)

#plot summer months over the years
June_indexes <- seq(6,186,12)
```

```
July_indexes <- seq(7,187,12)
August_indexes <- seq(8,188,12)
#merge the lists
summer_indexes <- c(June_indexes, July_indexes, August_indexes)
summer_indexes <- sort(summer_indexes)
#plot the rainfall in the summer months
plot(rainfall$Months[summer_indexes], rainfall$`Nedbør (mnd)`[summer_indexes], xlab = "Summer months",
    ylab = "Rainfall", type = "histogram")
#merge the rainfall of the summer months in one year to one variable
Jordal_rainfall_summer_months <- rainfall[summer_indexes,]
Jordal_rainfall_summer_2000 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[1:3])
Jordal_rainfall_summer_2001 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[4:6])
Jordal_rainfall_summer_2002 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[7:10])
Jordal_rainfall_summer_2003 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[10:12])
Jordal_rainfall_summer_2004 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[13:15])
Jordal_rainfall_summer_2005 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[16:18])
Jordal_rainfall_summer_2006 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[19:21])
Jordal_rainfall_summer_2007 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[22:24])
Jordal_rainfall_summer_2008 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[25:27])
Jordal_rainfall_summer_2009 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[28:30])
Jordal_rainfall_summer_2010 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[31:33])
Jordal_rainfall_summer_2011 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[34:36])
Jordal_rainfall_summer_2012 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[37:39])
Jordal_rainfall_summer_2013 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[40:42])
Jordal_rainfall_summer_2014 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[43:45])
Jordal_rainfall_summer_2015 <- sum(Jordal_rainfall_summer_months$`Nedbør (mnd)`[46:48])
Jordal_rainfall_summer_00_15 <- c(Jordal_rainfall_summer_2000,Jordal_rainfall_summer_2001,Jordal_rainfall_summer_2002,Jordal_rainfall_summer_2003,
                    Jordal_rainfall_summer_2004,Jordal_rainfall_summer_2005,Jordal_rainfall_summer_2006,Jordal_rainfall_summer_2007,
                    Jordal_rainfall_summer_2008,Jordal_rainfall_summer_2009,Jordal_rainfall_summer_2010,Jordal_rainfall_summer_2011,
                    Jordal_rainfall_summer_2012,Jordal_rainfall_summer_2013,Jordal_rainfall_summer_2014,Jordal_rainfall_summer_2015)
#plot the temperature in the summer months
plot(years[1:16], Jordal_rainfall_summer_00_15, xlab = "summer",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Jordalsvatnet")

#plot spring months over the years
March_indexes <- seq(3,183,12)
April_indexes <- seq(4,184,12)
May_indexes <- seq(5,185,12)
#merge the lists
spring_indexes <- c(March_indexes, April_indexes, May_indexes)
spring_indexes <- sort(spring_indexes)
length(spring_indexes)
#plot the rainfall in the spring months
plot(rainfall$Months[spring_indexes], rainfall$`Nedbør (mnd)`[spring_indexes], xlab = "Spring months",
    ylab = "Rainfall", type = "histogram")

#merge the rainfall of the summer months in one year to one variable
Jordal_rainfall_spring_months <- rainfall[spring_indexes,]
Jordal_rainfall_spring_2000 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[1:3])
Jordal_rainfall_spring_2001 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[4:6])
Jordal_rainfall_spring_2002 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[7:10])
Jordal_rainfall_spring_2003 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[10:12])
Jordal_rainfall_spring_2004 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[13:15])
Jordal_rainfall_spring_2005 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[16:18])
Jordal_rainfall_spring_2006 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[19:21])
Jordal_rainfall_spring_2007 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[22:24])
Jordal_rainfall_spring_2008 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[25:27])
Jordal_rainfall_spring_2009 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[28:30])
Jordal_rainfall_spring_2010 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[31:33])
Jordal_rainfall_spring_2011 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[34:36])
Jordal_rainfall_spring_2012 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[37:39])
Jordal_rainfall_spring_2013 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[40:42])
Jordal_rainfall_spring_2014 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[43:45])
Jordal_rainfall_spring_2015 <- sum(Jordal_rainfall_spring_months$`Nedbør (mnd)`[46:48])
Jordal_rainfall_spring_00_15 <- c(Jordal_rainfall_spring_2000,Jordal_rainfall_spring_2001,Jordal_rainfall_spring_2002,Jordal_rainfall_spring_2003,
                         Jordal_rainfall_spring_2004,Jordal_rainfall_spring_2005,Jordal_rainfall_spring_2006,Jordal_rainfall_spring_2007,
                         Jordal_rainfall_spring_2008,Jordal_rainfall_spring_2009,Jordal_rainfall_spring_2010,Jordal_rainfall_spring_2011,
                         Jordal_rainfall_spring_2012,Jordal_rainfall_spring_2013,Jordal_rainfall_spring_2014,Jordal_rainfall_spring_2015)
#plot the temperature in the summer months
plot(years[1:16], Jordal_rainfall_spring_00_15, xlab = "spring",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Jordalsvatnet")

#plot fall months over the years
Sept_indexes <- seq(9,189,12)
Oct_indexes <- seq(10,190,12)
Nov_indexes <- seq(11,191,12)
#merge the lists
fall_indexes <- c(Sept_indexes, Oct_indexes, Nov_indexes)
fall_indexes <- sort(fall_indexes)
length(fall_indexes)
#plot the rainfall in the fall months
plot(rainfall$Months[fall_indexes], rainfall$`Nedbør (mnd)`[fall_indexes], xlab = "fall months",
    ylab = "Rainfall", type = "histogram")
#merge the rainfall of the summer months in one year to one variable
Jordal_rainfall_fall_months <- rainfall[fall_indexes,]
Jordal_rainfall_fall_2000 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[1:3])
Jordal_rainfall_fall_2001 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[4:6])
Jordal_rainfall_fall_2002 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[7:10])
Jordal_rainfall_fall_2003 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[10:12])
Jordal_rainfall_fall_2004 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[13:15])
Jordal_rainfall_fall_2005 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[16:18])
Jordal_rainfall_fall_2006 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[19:21])
Jordal_rainfall_fall_2007 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[22:24])
Jordal_rainfall_fall_2008 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[25:27])
Jordal_rainfall_fall_2009 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[28:30])
Jordal_rainfall_fall_2010 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[31:33])
Jordal_rainfall_fall_2011 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[34:36])
Jordal_rainfall_fall_2012 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[37:39])
Jordal_rainfall_fall_2013 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[40:42])
Jordal_rainfall_fall_2014 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[43:45])
Jordal_rainfall_fall_2015 <- sum(Jordal_rainfall_fall_months$`Nedbør (mnd)`[46:48])
```

```
Jordal_rainfall_fall_00_15 <- c(Jordal_rainfall_fall_2000,Jordal_rainfall_fall_2001,Jordal_rainfall_fall_2002,Jordal_rainfall_fall_2003,
                              Jordal_rainfall_fall_2004,Jordal_rainfall_fall_2005,Jordal_rainfall_fall_2006,Jordal_rainfall_fall_2007,
                              Jordal_rainfall_fall_2008,Jordal_rainfall_fall_2009,Jordal_rainfall_fall_2010,Jordal_rainfall_fall_2011,
                              Jordal_rainfall_fall_2012,Jordal_rainfall_fall_2013,Jordal_rainfall_fall_2014,Jordal_rainfall_fall_2015)
#plot the temperature in the summer months
plot(years[1:16], Jordal_rainfall_fall_00_15, xlab = "fall",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Jordalsvatnet")


#plot winter months over the years
Dec_indexes <- seq(6,186,12)
Jan_indexes <- seq(7,187,12)
Feb_indexes <- seq(8,188,12)
#merge the lists
summer_indexes <- c(June_indexes, July_indexes, August_indexes)
summer_indexes <- sort(summer_indexes)
length(summer_indexes)
#plot the rainfall in the summer months
plot(1:length(summer_indexes), rainfall$`Nedbør (mnd)`[summer_indexes], xlab = "Summer",
    ylab = "Rainfall", type = "histogram")

#fit a model for rainfall against days
prec_days_poly1 <- lm(`Nedbør (mnd)`~Months, data = rainfall)
summary(prec_days_poly1)

#read in temperature data. Further I want to read in the additional weather data
temp_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "1. B Jordalsvatnet_online")
temp_poly <- lm(Temp~1, data = temp_data)
plot(temp_data$...1 ,temp_data$Temp)

#read in day temperature data from the excel file downloaded from Norsk Klimaservice
temp_data_day <- read_excel("Jordalsvatnet_temp.xlsx")
#plot the temperature over time to get an overview of the data
temp_data_day <- na.omit(temp_data_day) #get rid of NA values
plot(1:nrow(temp_data_day),temp_data_day$`Middeltemperatur (døgn)`, xlab = "Days from 1999",
    ylab = "Mean temperature of day", cex = 0.75, pch = 20, main = "Jordalsvatnet")

#plot summer months over the years
number_summer_days <- 91
summer_temp_2000 <- temp_data_day$`Middeltemperatur (døgn)`[518:(518+number_summer_days)]
summer_temp_2001 <- temp_data_day$`Middeltemperatur (døgn)`[883:(883+number_summer_days)]
summer_temp_2002 <- temp_data_day$`Middeltemperatur (døgn)`[1248:(1248+number_summer_days)]
summer_temp_2003 <- temp_data_day$`Middeltemperatur (døgn)`[1613:(1613+number_summer_days)]
summer_temp_2004 <- temp_data_day$`Middeltemperatur (døgn)`[1979:(1979+number_summer_days)]
summer_temp_2005 <- temp_data_day$`Middeltemperatur (døgn)`[2344:(2344+number_summer_days)]
summer_temp_2006 <- temp_data_day$`Middeltemperatur (døgn)`[2709:(2709+number_summer_days)]
summer_temp_2007 <- temp_data_day$`Middeltemperatur (døgn)`[3074:(3074+number_summer_days)]
summer_temp_2008 <- temp_data_day$`Middeltemperatur (døgn)`[3440:(3440+number_summer_days)]
summer_temp_2009 <- temp_data_day$`Middeltemperatur (døgn)`[3805:(3805+number_summer_days)]
summer_temp_2010 <- temp_data_day$`Middeltemperatur (døgn)`[4170:(4170+number_summer_days)]
summer_temp_2011 <- temp_data_day$`Middeltemperatur (døgn)`[4535:(4535+number_summer_days)]
summer_temp_2012 <- temp_data_day$`Middeltemperatur (døgn)`[4901:(4901+number_summer_days)]
summer_temp_2013 <- temp_data_day$`Middeltemperatur (døgn)`[5266:(5266+number_summer_days)]
summer_temp_2014 <- temp_data_day$`Middeltemperatur (døgn)`[5631:(5631+number_summer_days)]
summer_temp_2015 <- temp_data_day$`Middeltemperatur (døgn)`[5996:(5996+number_summer_days)]
#merge the lists
summer_temps_00_15 <- c(summer_temp_2000,summer_temp_2001,summer_temp_2002,summer_temp_2003,
                    summer_temp_2004,summer_temp_2005,summer_temp_2006,summer_temp_2007,
                    summer_temp_2008,summer_temp_2009,summer_temp_2010,summer_temp_2011,
                    summer_temp_2012,summer_temp_2013,summer_temp_2014,summer_temp_2015)
#plot the temperature in the summer months
plot(1:length(summer_temps_00_15), summer_temps_00_15, xlab = "Summer days from 2000",
    ylab = "Temperature", type = "l")
#compute the mean temperature of each summer
summer_mean_temp_00_15 = c(mean(summer_temp_2000),mean(summer_temp_2001),mean(summer_temp_2002),
                      mean(summer_temp_2003),mean(summer_temp_2004),mean(summer_temp_2005),
                      mean(summer_temp_2006),mean(summer_temp_2007),mean(summer_temp_2008),
                      mean(summer_temp_2009),mean(summer_temp_2010),mean(summer_temp_2011),
                      mean(summer_temp_2012),mean(summer_temp_2013),mean(summer_temp_2014),
                      mean(summer_temp_2015))
#plot the mean summer temperature against year
plot(years[1:16], summer_mean_temp_00_15, xlab = "Summer", ylab = "Mean summer temperature (°C)",
    type = "l", ylim = c(12,18), lwd = 2, main = "Jordalsvatnet")
#fit a model of mean summer temperature against year
summer_mean_temp_year_poly1 <- lm(summer_mean_temp_00_15~years_list)
summary(summer_mean_temp_year_poly1)

#look at winter temperatures
number_winter_days <- 89
winter_temp_1999 <- temp_data_day$`Middeltemperatur (døgn)`[1:59]
winter_temp_2000 <- temp_data_day$`Middeltemperatur (døgn)`[335:(335+90)]
winter_temp_2001 <- temp_data_day$`Middeltemperatur (døgn)`[701:(701+number_winter_days)]
winter_temp_2002 <- temp_data_day$`Middeltemperatur (døgn)`[1066:(1066+number_winter_days)]
winter_temp_2003 <- temp_data_day$`Middeltemperatur (døgn)`[1431:(1431+number_winter_days)]
winter_temp_2004 <- temp_data_day$`Middeltemperatur (døgn)`[1796:(1796+90)]
winter_temp_2005 <- temp_data_day$`Middeltemperatur (døgn)`[2162:(2162+number_winter_days)]
winter_temp_2006 <- temp_data_day$`Middeltemperatur (døgn)`[2527:(2527+number_winter_days)]
winter_temp_2007 <- temp_data_day$`Middeltemperatur (døgn)`[2892:(2892+number_winter_days)]
winter_temp_2008 <- temp_data_day$`Middeltemperatur (døgn)`[3257:(3257+90)]
winter_temp_2009 <- temp_data_day$`Middeltemperatur (døgn)`[3623:(3623+number_winter_days)]
winter_temp_2010 <- temp_data_day$`Middeltemperatur (døgn)`[3988:(3988+number_winter_days)]
winter_temp_2011 <- temp_data_day$`Middeltemperatur (døgn)`[4353:(4353+number_winter_days)]
winter_temp_2012 <- temp_data_day$`Middeltemperatur (døgn)`[4718:(4718+90)]
winter_temp_2013 <- temp_data_day$`Middeltemperatur (døgn)`[5084:(5084+number_winter_days)]
winter_temp_2014 <- temp_data_day$`Middeltemperatur (døgn)`[5449:(5449+number_winter_days)]
winter_temp_2015 <- temp_data_day$`Middeltemperatur (døgn)`[5814:(5814+number_winter_days)]
#merge the lists
winter_temps_00_15 <- c(mean(winter_temp_1999), mean(winter_temp_2000),mean(winter_temp_2001),
                    mean(winter_temp_2002),mean(winter_temp_2003),mean(winter_temp_2004),
                    mean(winter_temp_2005),mean(winter_temp_2006),mean(winter_temp_2007),
                    mean(winter_temp_2008),mean(winter_temp_2009),mean(winter_temp_2010),
```

```
                       mean(winter_temp_2011),mean(winter_temp_2012),mean(winter_temp_2013),
                       mean(winter_temp_2014),mean(winter_temp_2015))
plot(seq(1999,2015,1), winter_temps_00_15, xlab = "winter year", ylab = "mean winter temperature (°C)",
     type = "l", ylim = c(-3,7), lwd = 2, main = "Jordalsvatnet")
Jordal_winter_temp_matrix <- data.frame(seq(1999,2015,1),winter_temps_00_15)
colnames(Jordal_winter_temp_matrix) <- c("Year","Temperature")
Jordal_winter_temp_TS <- mblm(Temperature~Year, dataframe = Jordal_winter_temp_matrix, repeated = F)
summary(Jordal_winter_temp_TS)

#plot spring months over the years
number_spring_days <- 91
spring_temp_2000 <- temp_data_day$`Middeltemperatur (døgn)`[426:(426+number_spring_days)]
spring_temp_2001 <- temp_data_day$`Middeltemperatur (døgn)`[791:(791+number_spring_days)]
spring_temp_2002 <- temp_data_day$`Middeltemperatur (døgn)`[1156:(1156+number_spring_days)]
spring_temp_2003 <- temp_data_day$`Middeltemperatur (døgn)`[1521:(1521+number_spring_days)]
spring_temp_2004 <- temp_data_day$`Middeltemperatur (døgn)`[1887:(1887+number_spring_days)]
spring_temp_2005 <- temp_data_day$`Middeltemperatur (døgn)`[2252:(2252+number_spring_days)]
spring_temp_2006 <- temp_data_day$`Middeltemperatur (døgn)`[2617:(2617+number_spring_days)]
spring_temp_2007 <- temp_data_day$`Middeltemperatur (døgn)`[2982:(2982+number_spring_days)]
spring_temp_2008 <- temp_data_day$`Middeltemperatur (døgn)`[3348:(3348+number_spring_days)]
spring_temp_2009 <- temp_data_day$`Middeltemperatur (døgn)`[3713:(3713+number_spring_days)]
spring_temp_2010 <- temp_data_day$`Middeltemperatur (døgn)`[4078:(4078+number_spring_days)]
spring_temp_2011 <- temp_data_day$`Middeltemperatur (døgn)`[4443:(4443+number_spring_days)]
spring_temp_2012 <- temp_data_day$`Middeltemperatur (døgn)`[4809:(4809+number_spring_days)]
spring_temp_2013 <- temp_data_day$`Middeltemperatur (døgn)`[5174:(5174+number_spring_days)]
spring_temp_2014 <- temp_data_day$`Middeltemperatur (døgn)`[5539:(5539+number_spring_days)]
spring_temp_2015 <- temp_data_day$`Middeltemperatur (døgn)`[5904:(5904+number_spring_days)]
#merge the lists
spring_temps_00_15 <- c(spring_temp_2000,spring_temp_2001,spring_temp_2002,spring_temp_2003,
                        spring_temp_2004,spring_temp_2005,spring_temp_2006,spring_temp_2007,
                        spring_temp_2008,spring_temp_2009,spring_temp_2010,spring_temp_2011,
                        spring_temp_2012,spring_temp_2013,spring_temp_2014,spring_temp_2015)
#plot the temperature in the spring months
plot(1:length(spring_temps_00_15), spring_temps_00_15, xlab = "spring days from 2000",
     ylab = "Temperature", type = "l")
#compute the mean temperature of each spring
spring_mean_temp_00_15 = c(mean(spring_temp_2000),mean(spring_temp_2001),mean(spring_temp_2002),
                          mean(spring_temp_2003),mean(spring_temp_2004),mean(spring_temp_2005),
                          mean(spring_temp_2006),mean(spring_temp_2007),mean(spring_temp_2008),
                          mean(spring_temp_2009),mean(spring_temp_2010),mean(spring_temp_2011),
                          mean(spring_temp_2012),mean(spring_temp_2013),mean(spring_temp_2014),
                          mean(spring_temp_2015))
#plot the mean summer temperature against year
plot(years[1:16], spring_mean_temp_00_15, xlab = "spring", ylab = "mean spring temperature (°C)",
     type = "l", ylim = c(5,10), lwd = 2, main = "Jordalsvatnet")
#fit a model of mean summer temperature against year
summer_mean_temp_year_poly1 <- lm(summer_mean_temp_00_15~years_list)
summary(summer_mean_temp_year_poly1)


#checking whether the growing season is extended
get_growing_season <- function(temp_list, start_year, stop_year){
  days_growing_season <- c()
  for (year in start_year:stop_year){
    if (year == 2000 | year == 2004 | year == 2008 | year == 2012){
      days_in_year <- 366
    }else {
      days_in_year <- 365
    }
    temp_year <- temp_list[grepl(as.character(year),temp_list$`Tid(norsk normaltid)`),]
    print(temp_year)
    temp_pre_summer_reversed <- temp_year[200:1,]
    print(temp_pre_summer_reversed)
    start_date <- which(temp_pre_summer_reversed$`Middeltemperatur (døgn)` <5)[1]
    temp_post_summer <- temp_year[200:days_in_year,]
    print("før sommer")
    print("etter sommer")
    stop_date <- which(temp_post_summer$`Middeltemperatur (døgn)`<5)[1]
    days <- stop_date+start_date-1
    days_growing_season <- c(days_growing_season, days)
  }
  return(days_growing_season)
}

#checking whether the growing season is extended
Jordal_growing_season <- get_growing_season(temp_data_day,2000,2015)
plot(seq(2000,2015,1), Jordal_growing_season, type = "l", lwd = 2, main = "Jordalsvatnet",
     xlab = "year", ylab = "days in growing season", ylim = c(150,250), xaxt = "n")
axis(1, at = seq(2000,2015,1))

#read in year temperature data from the excel file from Norsk klimaservicesenter
temp_data_year <- read_excel("Jordalsvatnet_temp_year.xlsx")
temp_data_year <- na.omit(temp_data_year)
temp_data_year$Year <- years[1:16]
temp_data_year$Num_year <- as.numeric(temp_data_year$Year)
#fit a model for temperature against year
temp_year_poly1 <- lm(`Middeltemperatur (år)`~Num_year, temp_data_year)
summary(temp_year_poly1)

#fit a Theil-sen estimator for temperature against year
temp_year_poly1_TS <- mblm(`Middeltemperatur (år)`~Num_year, dataframe = temp_data_year, repeated = FALSE)
summary(temp_year_poly1_TS)

predictions <- predict.lm(object = temp_year_poly1)
plot(temp_data_year$`Tid(norsk normaltid)`, temp_data_year$`Middeltemperatur (år)`, ylim = c(4,12),
     xlab = "Year", ylab = "Mean temperature (°C)", lwd = 3, type = "l", main = "Jordalsvatnet" )
lines(temp_data_year$`Tid(norsk normaltid)`, predictions)

#fit a model for color as a function of annual mean temperature
color_temp_model <- lm(water_table_00_15$`Mean color`~temp_data_year$`Middeltemperatur (år)`)
summary(color_temp_model)
```

```
predictions <- predict.lm(object = color_temp_model) #predict in order to plot fitted line
plot(temp_data_year$`Middeltemperatur (år)`, water_table_00_15$`Mean color`,
     xlab = "Mean temperature (°C)", ylab = "Color (mg Pt/l)", cex = 0.75, pch = 20)
lines(temp_data_year$`Middeltemperatur (år)`, predictions, col = "red", lwd = 3)

#now I want to fit a model of acid deposition affecting color
sulfate_color_model <- lm(water_table_00_15$`Mean color`~poly(Jordalsvatnet_acid$SO4,1))
summary(sulfate_color_model)
sulfate_predictions <- predict.lm(sulfate_color_model)
lines(Jordalsvatnet_acid$SO4, sulfate_predictions)

#---------------Fit multiple linear regression model, with 4 variables, temperature,
#---------------rainfall, NDVI and acid rain.---------------
setwd("M:/Master thesis/Waterwork data")

#get the color values
water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
water_data <- na.omit(water_data) #get rid of the NA values
water_data <- water_data[7:nrow(water_data),] #in order to discard the year 1999
colnames(water_data) <- c("Date","Color")
water_data$Color <- as.numeric(water_data$Color) #make color data numeric
water_data <- water_data[order(water_data$Date),] #sort the data on date
water_data$Num_date <- as.numeric((water_data$Date))

Jordal_color_00_15 <- annual_color(water_data, 2000, 2015)

#need to make NDVI table, use read_ndvi for Jordalsvatnet to get NDVi values
#need to make acid tables, use read_ndvi for Jordalsvatnet to get
#Jordalsvatnet_shape_NO3 and Jordalsvatnet_shape_SO4.

#need to get the temperature
Jordalsvatnet_temp_year <- read_excel("Jordalsvatnet_temp_year.xlsx")
Jordalsvatnet_temp_year <- na.omit(Jordalsvatnet_temp_year)
Jordalsvatnet_temp_year$Year <- years[1:16]
Jordalsvatnet_temp_year$Num_year <- as.numeric(Jordalsvatnet_temp_year$Year)

#need to get the rainfall
Jordalsvatnet_rainfall_year <- read_excel("Jordalsvatnet_rainfall_year.xlsx")
Jordalsvatnet_rainfall_year <- na.omit(Jordalsvatnet_rainfall_year)
Jordalsvatnet_rainfall_year$Årsnedbør <- as.numeric(Jordalsvatnet_rainfall_year$Årsnedbør) #convert to numeric
Jordalsvatnet_rainfall_year$Year <- years[1:16]

#need to get length of growing season
temp_data_day <- read_excel("Jordalsvatnet_temp.xlsx")
#plot the temperature over time to get an overview of the data
temp_data_day <- na.omit(temp_data_day) #get rid of NA values
Jordal_growing_season <- get_growing_season(temp_data_day,2000,2015)
Jordal_growing_season_poly1 <- lm(Jordal_growing_season~years[1:16])
summary(Jordal_growing_season_poly1)

Jordal_growing_season_matrix <- data.frame(Jordal_growing_season, seq(2000,2015,1))
colnames(Jordal_growing_season_matrix) <- c("Days","Year")
Jordal_growing_season_TS <- mblm(Days~Year, dataframe = Jordal_growing_season_matrix, repeated = F)
summary(Jordal_growing_season_TS)

#--------------fit seasonal Kendall--------------
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "1. B Jordalsvatnet")

#get the color values
water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
water_data <- na.omit(water_data) #get rid of the NA values
water_data <- water_data[7:nrow(water_data),] #in order to discard the year 1999
colnames(water_data) <- c("Date","Color")
water_data$Color <- as.numeric(water_data$Color) #make color data numeric

water_data <- water_data[order(water_data$Date),] #sort the data on date
water_data$Num_date <- as.numeric((water_data$Date))

#see if data is normally distributed
hist(water_data$Color, breaks = seq(0,40,0.1))
water_data$Log_color <- log(water_data$Color)
hist(water_data$Log_color, breaks = seq(0,5,0.1))

#now we want to create a new column with year as a numeric variable
#create function for identifying the year in the date list
find_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,1,4) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

find_month <- function(date_list){
  month_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    month_col <- append(month_col, date_string)
  }
  month_col <- as.numeric(month_col)
  return(month_col)
}

find_season <- function(date_list){
  season_col <- c()
  for (i in 1:length(date_list)){
```

```
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
      date_string <- 2
    }
    else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
      date_string <- 3
    }
    else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
      date_string <- 4
    }
    else {
      date_string <- 1
    }
    season_col <- append(season_col, date_string)
  }
  return(season_col)
}

Jordal_year_col <- find_year(water_data$Date)
water_data$Year <- Jordal_year_col

Jordal_month_col <- find_month(water_data$Date)
water_data$Month <- Jordal_month_col

Jordal_season_col <- find_season(water_data$Date)
water_data$Season <- Jordal_season_col

#function for changing December months to be associated with January/February the year after
change_december <- function(water_table){   #takes in the entire matrix
  index_of_december <- water_table$Month == 12
  print(index_of_december)
  water_table$Year[index_of_december] <- water_table$Year[index_of_december] + 1
  return(water_table)
  }
water_data <- change_december(water_data)

#write matrix with date, colour, temperature and rainfall to csv file
Jordal_color_temperature2$Rainfall <- Jordal_color_rainfall$Rainfall
write_xlsx(Jordal_color_temperature2, "Jordalsvatnet_Date_Color_Temperature_Rainfall.xlsx")

#perform seasonal Kendall test
Jordal_SK_model <- kendallSeasonalTrendTest(y = water_data$Color, season = water_data$Season, year = water_data$Year)
Jordal_SK_model
summary(Jordal_SK_model)
Jordal_SK_model$seasonal.estimates

#perform another seasonal Kendall test with 4 seasons
Jordal_SK_rkt_1 <- rkt(date = water_data$Year, y = water_data$Color, block = water_data$Season, rep = "a")
#look at the model values
Jordal_SK_rkt_1
Jordal_SK_rkt_1$tau
Jordal_SK_rkt_1$sl

#perform another seasonal Kendall test with 4 seasons
Jordal_SK_rkt_2 <- rkt(date = water_data$Year, y = water_data$Color, block = water_data$Month, rep = "a")
#look at the model values
Jordal_SK_rkt_2
Jordal_SK_rkt_2$tau
Jordal_SK_rkt_2$sl

#fit a T-test adjusted for seasonality (TAS), linear regression with year and season as factors
Jordal_TAS_1 <- lm(Color~ (Year) + as.factor(Season), data = water_data)
summary(Jordal_TAS_1)

plot(water_data$Date, water_data$Color, xlab = "date", ylab = "colour (mg Pt/l)",
     cex = 0.75, pch = 20, main = "Jordalsvatnet")
#now make predictions manually
intercept_list <- water_data$Color-Jordal_SK_rkt_1$B*(water_data$Year-2000)
intercept <- median(intercept_list)
Jordal_SK_predictions <- intercept + Jordal_SK_rkt_1$B*seq(0,15,1)
lines(years[1:16], Jordal_SK_predictions, col = "red", lwd = 3)

#fit SK and TAS models for rainfall for Jordalsvatnet
Jordal_rainfall_months <- read_excel("Jordalsvatnet_rainfall.xlsx")
Jordal_rainfall_months <- na.omit(Jordal_rainfall_months)
Jordal_rainfall_months$`Nedbør (mnd)` <- as.numeric(Jordal_rainfall_months$`Nedbør (mnd)`) #make rainfall numeric in order to calculate

#find season in Jordal rainfall
find_rainfall_season <- function(date_list){
  season_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,1,2) #get the 4 first characters, which corresponds to year
    if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
      date_string <- 2
    }
    else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
      date_string <- 3
    }
    else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
      date_string <- 4
    }
    else {
      date_string <- 1
    }
    season_col <- append(season_col, date_string)
  }
  return(season_col)
}
find_rainfall_year <- function(date_list){
```

```
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,4,7) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

find_rainfall_month <- function(date_list){
  month_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,1,2) #get the 4 first characters, which corresponds to year
    month_col <- append(month_col, date_string)
  }
  month_col <- as.numeric(month_col)
  return(month_col)
}

Jordal_rainfall_months$Season <- find_rainfall_season(Jordal_rainfall_months$`Tid(norsk normaltid)`)
Jordal_rainfall_months$Year <- find_rainfall_year(Jordal_rainfall_months$`Tid(norsk normaltid)`)
Jordal_rainfall_months$Month <- find_rainfall_month(Jordal_rainfall_months$`Tid(norsk normaltid)`)

#make a function for making a rainfall column in the color matrix
Jordal_rainfall_correlation <- function(color_table, rainfall_table){
  color_table$Rainfall <- seq(1,nrow(color_table),1)
  for (i in (1:nrow(color_table))){
    year <- color_table$Year[i]
    month <- color_table$Month[i]
    color_table$Rainfall[i] <- rainfall_table$`Nedbør (mnd)`[(rainfall_table$Year == year) & (rainfall_table$Month == month)]
  }
  return(color_table)
}
Jordal_color_rainfall <- Jordal_rainfall_correlation(water_data, Jordal_rainfall_months)
#compute correlation between color and rainfall
cor(Jordal_color_rainfall$Color, Jordal_color_rainfall$Rainfall)

#make correlations for the four different seasons
color_winter <- Jordal_color_rainfall$Color[Jordal_color_rainfall$Season == 1]
rainfall_winter <- Jordal_color_rainfall$Rainfall[Jordal_color_rainfall$Season == 1]
cor(color_winter, rainfall_winter)
plot(rainfall_winter, color_winter)

color_spring <- Jordal_color_rainfall$Color[Jordal_color_rainfall$Season == 2]
rainfall_spring <- Jordal_color_rainfall$Rainfall[Jordal_color_rainfall$Season == 2]
cor(color_spring, rainfall_spring)
plot(rainfall_spring, color_spring)

color_summer <- Jordal_color_rainfall$Color[Jordal_color_rainfall$Season == 3]
rainfall_summer <- Jordal_color_rainfall$Rainfall[Jordal_color_rainfall$Season == 3]
cor(color_summer, rainfall_summer)
plot(rainfall_summer, color_summer)

color_fall <- Jordal_color_rainfall$Color[Jordal_color_rainfall$Season == 4]
rainfall_fall <- Jordal_color_rainfall$Rainfall[Jordal_color_rainfall$Season == 4]
cor(color_fall, rainfall_fall)
plot(rainfall_fall, color_fall)

#define a dataframe containing only the variables we want
Jordal_color_rainfall_month <- data.frame(Jordal_color_rainfall$Color,Jordal_color_rainfall$Rainfall,Jordal_color_rainfall$Month)
colnames(Jordal_color_rainfall_month) <- c("Color", "Rainfall", "Month")
#see if the data is normally distributed
hist(Jordal_color_rainfall_month$Color, breaks = seq(0,40,2))
hist(Jordal_color_rainfall_month$Rainfall)
hist(Jordal_color_rainfall_month$Month)

cor_color_rainfall <- cor_test(Jordal_color_rainfall_month, "Color", "Rainfall", method = "pearson")
cor(Jordal_color_rainfall_month$Color, Jordal_color_rainfall_month$Rainfall)
pcor.test(Jordal_color_rainfall_month$Color, Jordal_color_rainfall_month$Rainfall, Jordal_color_rainfall_month$Month)
color_January <- Jordal_color_rainfall_month$Color[Jordal_color_rainfall_month$Month == 1]
rainfall_January <- Jordal_color_rainfall_month$Rainfall[Jordal_color_rainfall_month$Month == 1]
cor(color_January, rainfall_January)

#fit linear model
Jordal_color_rainfall_poly1 <- lm(Color~Rainfall,data = Jordal_color_rainfall)
summary(Jordal_color_rainfall_poly1)
plot(Jordal_color_rainfall$Rainfall, Jordal_color_rainfall$Color, xlab = "monthly rainfall (mm)", ylab = "colour (mg Pt/l)",
     cex = 0.75, pch = 20, main = "Jordalsvatnet")
lines(Jordal_color_rainfall$Rainfall,Jordal_color_rainfall_poly1$fitted.values, col = "red", lwd = 3)

#handle December in Jordal_rainfall_months
Jordal_rainfall_months <- change_december(Jordal_rainfall_months)
#fit SK model for rainfall
Jordal_SK_rkt_rainfall <- rkt(date = Jordal_rainfall_months$Year, y = Jordal_rainfall_months$`Nedbør (mnd)`, block = Jordal_rainfall_months$Season, rep = "a")
Jordal_SK_rkt_rainfall

#fit TAS model for rainfall
Jordal_TAS_rainfall <- lm(`Nedbør (mnd)`~ (Year) + as.factor(Season), data = Jordal_rainfall_months)
summary(Jordal_TAS_rainfall)

#plot daily rainfall for Jordalsvatnet
plot(Jordal_rainfall_months$`Tid(norsk normaltid)`, Jordal_rainfall_months$`Nedbør (mnd)`, xlab = "date (month)",
ylab = "rainfall (mm)", type = "h", main = "Jordalsvatnet")

#fit SK and TAS models for temperature for Jordalsvatnet
Jordal_temp_day <- read_excel("Jordalsvatnet_temp.xlsx")
#plot the temperature over time to get an overview of the data
Jordal_temp_day <- na.omit(Jordal_temp_day) #get rid of NA values
Jordal_temp_day <- Jordal_temp_day[366:nrow(Jordal_temp_day),] #remove obervations before 2000
```

```
find_temp_season <- function(date_list){
  season_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,4,5) #get the 4 first characters, which corresponds to year
    if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
      date_string <- 2
    }
    else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
      date_string <- 3
    }
    else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
      date_string <- 4
    }
    else {
      date_string <- 1
    }
    season_col <- append(season_col, date_string)
  }
  return(season_col)
}
find_temp_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,7,10) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}
find_temp_month <- function(date_list){
  month_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,4,5) #get the 4 first characters, which corresponds to year
    month_col <- append(month_col, date_string)
  }
  month_col <- as.numeric(month_col)
  return(month_col)
}

Jordal_temp_day$Year <- find_temp_year(Jordal_temp_day$`Tid(norsk normaltid)`)
Jordal_temp_day$Season <- find_temp_season(Jordal_temp_day$`Tid(norsk normaltid)`)
Jordal_temp_day$Month <- find_temp_month(Jordal_temp_day$`Tid(norsk normaltid)`)

#make a function for making a temperature column in the color matrix
Jordal_temperature_correlation <- function(color_table, temperature_table){
  color_table$Temperature <- seq(1,nrow(color_table),1)
  color_table$Date <- as.character(color_table$Date)
  new_date_character <- str_split(color_table$Date,"-")
  for (i in (1:nrow(color_table))){
    year_character <- new_date_character[[i]][1]
    month_character <- new_date_character[[i]][2]
    day_character <- new_date_character[[i]][3]
    new_date_character[[i]] <- paste(day_character, month_character, year_character, sep = ".")
  }
  new_date_character <- unlist(new_date_character)
  for (i in (1:nrow(color_table))){
    date_index <- match(new_date_character[i], temperature_table$`Tid(norsk normaltid)`)
    color_table$Temperature[i] <- mean(temperature_table$`Middeltemperatur (døgn)`[(date_index-6):date_index])
  }
  return(color_table)
}

Jordal_temperature_correlation <- function(color_table, temperature_table){
  color_table$Temperature <- seq(1,nrow(color_table),1) #make column
  for (i in (1:nrow(color_table))){
    year <- color_table$Year[i]
    month <- color_table$Month[i]
    color_table$Rainfall[i] <- rainfall_table$`Nedbør (mnd)`[(rainfall_table$Year == year) & (rainfall_table$Month == month)]
  }
  return(color_table)
}

Jordal_color_temperature <- Jordal_temperature_correlation(water_data, Jordal_temp_day)
Jordal_color_temperature2 <- Jordal_temperature_correlation(water_data, Jordal_temp_day)

#compute correlation between color and temperature
cor(Jordal_color_temperature$Color, Jordal_color_temperature$Temperature)
pcor.test(Jordal_color_temperature$Color, Jordal_color_temperature$Temperature, as.factor(Jordal_color_temperature$Month), method = "pearson")
plot(Jordal_color_temperature$Temperature, Jordal_color_temperature$Color)

#make correlations for the four different seasons
color_winter <- Jordal_color_temperature$Color[Jordal_color_temperature$Season == 1]
temperature_winter <- Jordal_color_temperature$Temperature[Jordal_color_temperature$Season == 1]
cor(color_winter, temperature_winter)
plot(temperature_winter, color_winter)

color_spring <- Jordal_color_temperature$Color[Jordal_color_temperature$Season == 2]
temperature_spring <- Jordal_color_temperature$Temperature[Jordal_color_temperature$Season == 2]
cor(color_spring, temperature_spring)
plot(temperature_spring, color_spring)

color_summer <- Jordal_color_temperature$Color[Jordal_color_temperature$Season == 3]
temperature_summer <- Jordal_color_temperature$Temperature[Jordal_color_temperature$Season == 3]
cor(color_summer, temperature_summer)
plot(temperature_summer, color_summer)

color_fall <- Jordal_color_temperature$Color[Jordal_color_temperature$Season == 4]
```

```
temperature_fall <- Jordal_color_temperature$Temperature[Jordal_color_temperature$Season == 4]
cor(color_fall, temperature_fall)
plot(temperature_fall, color_fall)

#fit linear model
Jordal_color_temperature_poly1 <- lm(Color~Temperature,data = Jordal_color_temperature2)
summary(Jordal_color_temperature_poly1)
plot(Jordal_color_temperature2$Temperature, Jordal_color_temperature2$Color, xlab = "mean weekly temperature (°C)", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Jordalsvatnet")
lines(Jordal_color_temperature2$Temperature, Jordal_color_temperature_poly1$fitted.values, col = "red", lwd = 3)

mean(Jordal_color_temperature$Color[Jordal_color_temperature$Season == 1])
mean(Jordal_color_temperature$Color[Jordal_color_temperature$Season == 2])
mean(Jordal_color_temperature$Color[Jordal_color_temperature$Season == 3])
mean(Jordal_color_temperature$Color[Jordal_color_temperature$Season == 4])

#fit a model that takes Month into account
Jordal_color_temperature_poly2 <- lm(Color~Temperature+as.factor(Month),data = Jordal_color_temperature)
summary(Jordal_color_temperature_poly2)

#handle December in Jordal_rainfall_months
Jordal_temp_day <- change_december(Jordal_temp_day)

#fit a  SK model for Jordal temp
Jordal_SK_rkt_temp <- rkt(date = Jordal_temp_day$Year, y = Jordal_temp_day$`Middeltemperatur (døgn)`, block = Jordal_temp_day$Season, rep = "a")
Jordal_SK_rkt_temp

#fit a TAS model for temperature
Jordal_TAS_temp <- lm(`Middeltemperatur (døgn)`~ (Year) + as.factor(Season), data = Jordal_temp_day)
summary(Jordal_TAS_temp)

#fit TAS and SK model for NDVI
#fit SK model
Jordal_SK_rkt_NDVI <- rkt(date = Jordalsvatnet_yearly_shape$year, y = Jordalsvatnet_yearly_shape$NDVI)
Jordal_SK_rkt_NDVI

#test a Theil-Sen estimator
Jordal_Mann_Kendall_rkt_NDVI <- mblm(NDVI~year, dataframe = Jordalsvatnet_yearly_shape, repeated = F)
summary(Jordal_Mann_Kendall_rkt_NDVI) #different result than SK model

#fit linear model (because there is no seasonality)
Jordal_TAS_temp <- lm(Jordalsvatnet_yearly_shape$NDVI~Jordalsvatnet_yearly_shape$year)
summary(Jordal_TAS_temp)

#plot temperature against date
Jordal_temperature_month_total <- function(matrix){
  list_month_total <- c()
  for (year in 2000:2015){
    for (month in 1:12){
      current_year_matrix <- matrix[matrix$Year == year,]
      actual_month <- current_year_matrix$`Middeltemperatur (døgn)`[current_year_matrix$Month == month]
      print(year)
      print(month)
      print(actual_month)
      month_total <- mean(actual_month)
      list_month_total <- append(list_month_total, month_total)
    }
  }
  return(list_month_total)
}

Jordal_temp_month <- Jordal_temperature_month_total(Jordal_temp_day)

x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=192), "%Y-%m-%d")
months <- as.Date(months)
plot(months, Jordal_temp_month, xlab = "date (monthly)",
    ylab = "mean temperature (°C)", type = "l", main = "Bergen (Jordalsvatnet)", col = "red", lwd = 2)

#plot NDVI
#now we plot mean NDVI values for each year, as a function of year
plot(Jordalsvatnet_yearly_shape$year, Jordalsvatnet_yearly_shape$NDVI, type = "l", ylim = c(0.4,0.8),
    ylab = "NDVI", xlab = "year", cex = 0.75, pch = 20, lwd = 3, main = "Jordalsvatnet", xaxt = "n")
axis(1, at = seq(1999,2015,1))
Jordal_NDVI_shape_predictions_TS <- predict.lm(Jordal_Mann_Kendall_rkt_NDVI)

#fit Theil-Sen estimator for SO4
Jordalsvatnet_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Jordalsvatnet_shape_SO4, repeated = FALSE)
summary(Jordalsvatnet_sulfate_year_poly1_TS)

Jordalsvatnet_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Jordalsvatnet_shape_NO3, repeated = FALSE)
summary(Jordalsvatnet_nitrate_year_poly1_TS)

plot(Jordalsvatnet_shape_SO4$Year, Jordalsvatnet_shape_SO4$SO4, type = "l", col = "red", ylim = c(0,1200),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Jordalsvatnet", xaxt = "n")
par(new = T)
plot(Jordalsvatnet_shape_NO3$Year, Jordalsvatnet_shape_NO3$NO3, type = "l", col = "green", ylim = c(0,1200),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Jordalsvatnet", xaxt = "n")
legend(2000, 300, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)
axis(1, at = seq(2000,2014,1))

predictions_sulfate_TS <- predict.lm(Jordalsvatnet_sulfate_year_poly1_TS)
lines(Jordalsvatnet_shape_SO4$Year, predictions_sulfate_TS, lwd = 3, col = "firebrick")
predictions_nitrate_TS <- predict.lm(Jordalsvatnet_nitrate_year_poly1_TS)
lines(Jordalsvatnet_shape_NO3$Year, predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#fit a linear model
Jordalsvatnet_sulfate_year_poly1 <- lm(Jordalsvatnet_shape_SO4$SO4~Jordalsvatnet_shape_SO4$Year)
summary(Jordalsvatnet_sulfate_year_poly1)

Jordalsvatnet_nitrate_year_poly1 <- lm(Jordalsvatnet_shape_NO3$NO3~Jordalsvatnet_shape_NO3$Year)
```

```
summary(Jordalsvatnet_nitrate_year_poly1)

predictions_sulfate <- predict.lm(Jordalsvatnet_sulfate_year_poly1)
lines(Jordalsvatnet_shape_SO4$Year, predictions_sulfate, lwd = 3, col = "firebrick")
predictions_nitrate <- predict.lm(Jordalsvatnet_nitrate_year_poly1)
lines(Jordalsvatnet_shape_NO3$Year, predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a mixed linear model of color as a function of SO4 and NO3
#first we have to collect the color into mean yearly values
Jordal_color_00_15 <- annual_color(water_data, 2000, 2015)
#add NO3 and SO4 to this model
Jordal_color_00_15$SO4 <- Jordalsvatnet_shape_SO4$SO4
Jordal_color_00_15$NO3 <- Jordalsvatnet_shape_NO3$NO3
colnames(Jordal_color_00_15) <- c("Year","Color","SO4","NO3")
#add modified Year column in order to fit felm model
Jordal_color_00_15$Year_mod <- Jordal_color_00_15$Year-2000

Jordal_scaled <- data.frame(scale(Jordal_color_00_15, center = TRUE, scale = TRUE))

#look at correlation between SO4 and NO3
cor(Jordal_color_00_15$SO4, Jordal_color_00_15$NO3)

#fit a linear regression model with year as control variable
Jordal_color_SO4_year <- lm(Color~SO4+Year,data = Jordal_color_00_15, scale = TRUE, center = TRUE)
summary(Jordal_color_SO4_year)

Jordal_color_SO4 <- lm(Color~SO4,data = Jordal_color_00_15, scale = TRUE, center = TRUE)
summary(Jordal_color_SO4)

Jordal_SO4_for_plot <- Jordal_color_00_15$SO4
#plot colour against sulphate
plot(Jordal_color_00_15$SO4, Jordal_color_00_15$Color,
    ylim = c(15,30), xlim = c(400,1200), xlab = "SO4 concentration (mg (S/N)/m^2)",
    ylab = "colour (mg Pt/L)", cex = 1.5, pch = 20, main = "Jordalsvatnet")
lines(Jordal_color_00_15$SO4, Jordal_color_SO4$fitted.values, lwd = 3,
     col = "red")

Jordal_color_SO4_scaled <- lm(Color~SO4,data = Jordal_scaled)
summary(Jordal_color_SO4_scaled)

Jordal_color_SO4_year_felm <- felm(Color~SO4|Year_mod, data = Jordal_color_00_15)
summary(Jordal_color_SO4_year_felm)

#fit a linear model with year as controlling variable
Jordal_color_SO4_year_control <- felm(b~c|e, data = Jordal_copy)
summary(Jordal_color_SO4_year_control)

calc.relimp(Jordal_color_SO4_NO3, type = c("lmg"), rela = TRUE)

#--------------PCA---------------
#gather the data for Jordal in one matrix
#define annual temperature and rainfall
Jordalsvatnet_rainfall_year <- read_excel("Jordalsvatnet_rainfall_year.xlsx")
Jordalsvatnet_rainfall_year <- na.omit(Jordalsvatnet_rainfall_year)
Jordalsvatnet_rainfall_year$Årsnedbør <- as.numeric(Jordalsvatnet_rainfall_year$Årsnedbør) #convert to numeric
Jordalsvatnet_rainfall_year$Year <- years[1:16]

Jordalsvatnet_temperature_year <- read_excel("Jordalsvatnet_temp_year.xlsx")
Jordalsvatnet_temperature_year <- na.omit(Jordalsvatnet_temperature_year)
Jordalsvatnet_temperature_year$`Middeltemperatur (år)` <- as.numeric(Jordalsvatnet_temperature_year$`Middeltemperatur (år)`) #convert to numeric
Jordalsvatnet_temperature_year$Year <- years[1:16]

#get a matrix of mean annual color. Remember to include december to the year after
Jordalsvatnet_annual_color <- annual_color(water_data, 2000,2015)

Jordal_matrix <- data.frame(Jordalsvatnet_annual_color,Jordalsvatnet_rainfall_year$Årsnedbør,
                        Jordalsvatnet_temperature_year$`Middeltemperatur (år)`,
                        Jordalsvatnet_yearly_shape$NDVI[1:16], Jordalsvatnet_shape_SO4$SO4)
colnames(Jordal_matrix) <- c("Year","Colour","Rainfall", "Temp", "NDVI", "SO4")
rownames <- seq(2000,2015,1)
rownames(Jordal_matrix) <- as.character(rownames)
write_xlsx(Jordal_matrix, "Jordal_PCA_matrix.xlsx")

Jordal_PCA <- prcomp(Jordal_matrix[,-1], scale=TRUE)
Jordal_PCA$rotation
autoplot(Jordal_PCA, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Jordalsvatnet", label = TRUE, label.size = 3, shape = F, scale = 0)
summary(Jordal_PCA)
Jordal_PCA$x

Jordal_PCA_noyear <- prcomp(Jordal_matrix[,-1], scale=TRUE)
Jordal_PCA_noyear$rotation[,2]
autoplot(Jordal_PCA_noyear, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Jordalsvatnet", label = TRUE, label.size = 3, shape = F, scale = 0)
summary(Jordal_PCA_no_year)
```

Glomma.R

```
#Analyzing data from NRV ----------------

library("readxl")
library("timetools")
library("mblm")
#read in the data
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "2. NRV Glomma")

#handling the data for date and color. Make a model for color vs date
NRV_water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
NRV_water_data <- na.omit(NRV_water_data) #get rid of the NA values
NRV_water_data <- NRV_water_data[51:nrow(NRV_water_data),] #go to year 2000
colnames(NRV_water_data) <- c("Date","Color")
NRV_water_data$Color <- as.numeric(NRV_water_data$Color) #make color data numeric
NRV_water_data <- NRV_water_data[order(NRV_water_data$Date),] #sort date in chronological order

#fit polynomial models of degree 1 on color vs days after January 1 2000
NRV_color_poly1 <- lm(Color~Date, data = NRV_water_data)
summary(NRV_color_poly1)
NRV_color_predictions <- predict.lm(NRV_color_poly1)
plot(NRV_water_data$Date, NRV_water_data$Color, xlab = "Date", ylab = "Colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Glomma")
lines(NRV_water_data$Date, NRV_color_predictions, lwd = 3, col = "red")

#fit Theil-Sen estimator
NRV_water_data$Num_date <- as.numeric(NRV_water_data$Date) #add column with Num_date
NRV_color_poly1_TS <- mblm(Color~Num_date, dataframe = NRV_water_data, repeated = FALSE)
summary(NRV_color_poly1_TS)
NRV_color_predictions_TS <- predict.lm(object = NRV_color_poly1_TS)
plot(NRV_water_data$Date, NRV_water_data$Color, xlab = "Date", ylab = "Colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "NRV")
lines(NRV_water_data$Date, NRV_color_predictions_TS, lwd = 3, col = "red")

#handling the data for date and color. Make a model for color vs date
NRV_water_data_TOC <- data.frame(water_data$Date, water_data$TOC, water_data$Color) #make a dataframe with only Date and Color
NRV_water_data_TOC <- na.omit(NRV_water_data_TOC) #get rid of the NA values
NRV_water_data_TOC <- NRV_water_data_TOC[20:nrow(NRV_water_data_TOC),]
colnames(NRV_water_data_TOC) <- c("Date","TOC","Color")
NRV_water_data_TOC$TOC <- as.numeric(NRV_water_data_TOC$TOC) #make TOC data numeric
NRV_water_data_TOC$Color <- as.numeric(NRV_water_data_TOC$Color) #make TOC data numeric
NRV_water_data_TOC <- NRV_water_data_TOC[order(NRV_water_data_TOC$Date),]

annual_TOC <- function(table, start_year, stop_year){
	TOC_mean <- c()
	year_list <- table$Date
	year_list <- POSIXst(year_list, "year")
	year_list <- year_list@subtime
	for (year in start_year:stop_year){
		TOC_mean <- append(TOC_mean, mean(table$TOC[year_list == year]))
	}
	new_water_table <- data.frame(start_year:stop_year, TOC_mean)
	colnames(new_water_table) <- c("Year", "Mean TOC")
	return(new_water_table)
}

#fit Theil-Sen estimator
NRV_water_data_TOC$Num_date <- as.numeric(NRV_water_data_TOC$Date) #add column with Num_date
NRV_TOC_poly1_TS <- mblm(TOC~Num_date, dataframe = NRV_water_data_TOC, repeated = FALSE)
summary(NRV_TOC_poly1_TS)
NRV_TOC_predictions_TS <- predict.lm(object = NRV_TOC_poly1_TS)
plot(NRV_water_data_TOC$Date, NRV_water_data_TOC$TOC, xlab = "Date", ylab = "TOC (mg/l)",
    cex = 0.75, pch = 20, main = "NRV")
lines(NRV_water_data_TOC$Date, NRV_TOC_predictions_TS, lwd = 3, col = "red")

#fit polynomial models of degree 1 on TOC vs date
TOC_date_model <- lm(TOC~Date, data = NRV_water_data_TOC)
summary(TOC_date_model)

TOC_predictions <- predict.lm(object = TOC_date_model)
#make scatter plot and plot of model
plot(NRV_water_data_TOC$Date, NRV_water_data_TOC$TOC, xlab = "Date", ylab = "TOC (mg/l)",
    cex = 0.75, pch = 20, main = "NRV")
lines(NRV_water_data_TOC$Date, TOC_predictions, col = "red", lwd = 3)

#investigate color against TOC
#first we want to plot color against TOC and look at the correlation
plot(NRV_water_data_TOC$TOC, NRV_water_data_TOC$Color, xlab = "TOC (mg/L)",
    ylab = "Colour (mg Pt/L)", cex = 0.75, pch = 20, main = "NRV")
cor(NRV_water_data_TOC$TOC, NRV_water_data_TOC$Color) #compute correlation

#add "Ratio" as a column
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "2. NRV Glomma")

#handling the data for date and color. Make a model for color vs date
NRV_water_data <- data.frame(water_data$Date, water_data$Color,water_data$`Color/DOC`) #make a dataframe with only Date and Color
NRV_water_data <- NRV_water_data[53:nrow(NRV_water_data),] #go to year 2000
NRV_water_data <- na.omit(NRV_water_data) #get rid of the NA values
colnames(NRV_water_data) <- c("Date","Color","Ratio")
NRV_water_data$Color <- as.numeric(NRV_water_data$Color) #make color data numeric
NRV_water_data <- NRV_water_data[order(NRV_water_data$Date),] #sort the data by dates
#fit a linear model of ratio vs date
NRV_ratio_poly1 <- lm(Ratio~Date, data = NRV_water_data)
summary(NRV_ratio_poly1)


#Now we want to look at rainfall in Sjoa over date
rainfall <- read_excel("Sjoa_rainfall.xlsx")
rainfall <- na.omit(rainfall)
```

```
rainfall$`Nedbør (mnd)` <- as.numeric(rainfall$`Nedbør (mnd)`)
x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=180), "%Y-%m-%d")
rainfall$Months <- as.POSIXct(months)
plot(rainfall$Months, rainfall$`Nedbør (mnd)`, xlab = "date (monthly)",
    ylab = "rainfall (mm)", type = "h", main = "Sjoa (Glomma)", col = "blue")

#fit a model for rainfall against days
prec_days_poly1 <- lm(`Nedbør (mnd)`~Months, data = rainfall)
summary(prec_days_poly1)

#define years list in order to plot season rainfall data for each year later
years <- c("2000-01-01","2001-01-01","2002-01-01","2003-01-01",
         "2004-01-01","2005-01-01","2006-01-01","2007-01-01","2008-01-01",
         "2009-01-01","2010-01-01","2011-01-01","2012-01-01","2013-01-01",
         "2014-01-01")
years = as.POSIXct(years)

#plot summer months over the years
June_indexes <- seq(6,176,12)
July_indexes <- seq(7,177,12)
August_indexes <- seq(8,178,12)
#merge the lists
summer_indexes <- c(June_indexes, July_indexes, August_indexes)
summer_indexes <- sort(summer_indexes)
#plot the rainfall in the summer months
plot(rainfall$Months[summer_indexes], rainfall$`Nedbør (mnd)`[summer_indexes], xlab = "Summer months",
    ylab = "Rainfall", type = "histogram")
#merge the rainfall of the summer months in one year to one variable
NRV_rainfall_summer_months <- rainfall[summer_indexes,]
NRV_rainfall_summer_2000 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[1:3])
NRV_rainfall_summer_2001 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[4:6])
NRV_rainfall_summer_2002 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[7:10])
NRV_rainfall_summer_2003 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[10:12])
NRV_rainfall_summer_2004 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[13:15])
NRV_rainfall_summer_2005 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[16:18])
NRV_rainfall_summer_2006 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[19:21])
NRV_rainfall_summer_2007 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[22:24])
NRV_rainfall_summer_2008 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[25:27])
NRV_rainfall_summer_2009 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[28:30])
NRV_rainfall_summer_2010 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[31:33])
NRV_rainfall_summer_2011 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[34:36])
NRV_rainfall_summer_2012 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[37:39])
NRV_rainfall_summer_2013 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[40:42])
NRV_rainfall_summer_2014 <- sum(NRV_rainfall_summer_months$`Nedbør (mnd)`[43:45])
NRV_rainfall_summer_00_14 <- c(NRV_rainfall_summer_2000,NRV_rainfall_summer_2001,NRV_rainfall_summer_2002,NRV_rainfall_summer_2003,
                            NRV_rainfall_summer_2004,NRV_rainfall_summer_2005,NRV_rainfall_summer_2006,NRV_rainfall_summer_2007,
                            NRV_rainfall_summer_2008,NRV_rainfall_summer_2009,NRV_rainfall_summer_2010,NRV_rainfall_summer_2011,
                            NRV_rainfall_summer_2012,NRV_rainfall_summer_2013,NRV_rainfall_summer_2014)
NRV_rainfall_summer_matrix <- data.frame(seq(2000,2014,1),NRV_rainfall_summer_00_14)
colnames(NRV_rainfall_summer_matrix) <- c("Year","Rainfall")
NRV_rainfall_summer_TS <- mblm(Rainfall~Year, dataframe = NRV_rainfall_summer_matrix, repeated = F)
summary(NRV_rainfall_summer_TS)

#plot the temperature in the summer months
plot(years[1:15], NRV_rainfall_summer_00_14, xlab = "summer",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "NRV")

#plot spring months over the years
March_indexes <- seq(3,171,12)
April_indexes <- seq(4,172,12)
May_indexes <- seq(5,173,12)
#merge the lists
spring_indexes <- c(March_indexes, April_indexes, May_indexes)
spring_indexes <- sort(spring_indexes)

#plot the rainfall in the spring months
plot(rainfall$Months[spring_indexes], rainfall$`Nedbør (mnd)`[spring_indexes], xlab = "spring months",
    ylab = "rainfall (mm)", type = "histogram")

#merge the rainfall of the summer months in one year to one variable
NRV_rainfall_spring_months <- rainfall[spring_indexes,]
NRV_rainfall_spring_2000 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[1:3])
NRV_rainfall_spring_2001 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[4:6])
NRV_rainfall_spring_2002 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[7:10])
NRV_rainfall_spring_2003 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[10:12])
NRV_rainfall_spring_2004 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[13:15])
NRV_rainfall_spring_2005 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[16:18])
NRV_rainfall_spring_2006 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[19:21])
NRV_rainfall_spring_2007 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[22:24])
NRV_rainfall_spring_2008 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[25:27])
NRV_rainfall_spring_2009 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[28:30])
NRV_rainfall_spring_2010 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[31:33])
NRV_rainfall_spring_2011 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[34:36])
NRV_rainfall_spring_2012 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[37:39])
NRV_rainfall_spring_2013 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[40:42])
NRV_rainfall_spring_2014 <- sum(NRV_rainfall_spring_months$`Nedbør (mnd)`[43:45])
NRV_rainfall_spring_00_14 <- c(NRV_rainfall_spring_2000,NRV_rainfall_spring_2001,NRV_rainfall_spring_2002,NRV_rainfall_spring_2003,
                            NRV_rainfall_spring_2004,NRV_rainfall_spring_2005,NRV_rainfall_spring_2006,NRV_rainfall_spring_2007,
                            NRV_rainfall_spring_2008,NRV_rainfall_spring_2009,NRV_rainfall_spring_2010,NRV_rainfall_spring_2011,
                            NRV_rainfall_spring_2012,NRV_rainfall_spring_2013,NRV_rainfall_spring_2014)
#plot the temperature in the summer months
plot(years[1:15], NRV_rainfall_spring_00_14, xlab = "spring",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "NRV")

#plot fall months over the years
Sept_indexes <- seq(9,189,12)
Oct_indexes <- seq(10,190,12)
Nov_indexes <- seq(11,191,12)
#merge the lists
fall_indexes <- c(Sept_indexes, Oct_indexes, Nov_indexes)
```

```
fall_indexes <- sort(fall_indexes)

#plot the rainfall in the fall months
plot(rainfall$Months[fall_indexes], rainfall$`Nedbør (mnd)`[fall_indexes], xlab = "fall months",
    ylab = "Rainfall", type = "histogram")
#merge the rainfall of the summer months in one year to one variable
NRV_rainfall_fall_months <- rainfall[fall_indexes,]
NRV_rainfall_fall_2000 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[1:3])
NRV_rainfall_fall_2001 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[4:6])
NRV_rainfall_fall_2002 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[7:10])
NRV_rainfall_fall_2003 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[10:12])
NRV_rainfall_fall_2004 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[13:15])
NRV_rainfall_fall_2005 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[16:18])
NRV_rainfall_fall_2006 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[19:21])
NRV_rainfall_fall_2007 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[22:24])
NRV_rainfall_fall_2008 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[25:27])
NRV_rainfall_fall_2009 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[28:30])
NRV_rainfall_fall_2010 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[31:33])
NRV_rainfall_fall_2011 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[34:36])
NRV_rainfall_fall_2012 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[37:39])
NRV_rainfall_fall_2013 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[40:42])
NRV_rainfall_fall_2014 <- sum(NRV_rainfall_fall_months$`Nedbør (mnd)`[43:45])

NRV_rainfall_fall_00_14 <- c(NRV_rainfall_fall_2000,NRV_rainfall_fall_2001,NRV_rainfall_fall_2002,NRV_rainfall_fall_2003,
                             NRV_rainfall_fall_2004,NRV_rainfall_fall_2005,NRV_rainfall_fall_2006,NRV_rainfall_fall_2007,
                             NRV_rainfall_fall_2008,NRV_rainfall_fall_2009,NRV_rainfall_fall_2010,NRV_rainfall_fall_2011,
                             NRV_rainfall_fall_2012,NRV_rainfall_fall_2013,NRV_rainfall_fall_2014)
#plot the temperature in the fall months
plot(years[1:15], NRV_rainfall_fall_00_14, xlab = "fall",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "NRV")

#plot winter months over the years
Dec_indexes <- seq(12,168,12)
Jan_indexes <- seq(13,169,12)
Feb_indexes <- seq(14,170,12)
#merge the lists
winter_indexes <- c(Dec_indexes, Jan_indexes, Feb_indexes)
winter_indexes <- sort(winter_indexes)

NRV_rainfall_winter_months <- rainfall[winter_indexes,]
NRV_rainfall_winter_2000 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[1:3])
NRV_rainfall_winter_2001 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[4:6])
NRV_rainfall_winter_2002 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[7:10])
NRV_rainfall_winter_2003 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[10:12])
NRV_rainfall_winter_2004 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[13:15])
NRV_rainfall_winter_2005 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[16:18])
NRV_rainfall_winter_2006 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[19:21])
NRV_rainfall_winter_2007 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[22:24])
NRV_rainfall_winter_2008 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[25:27])
NRV_rainfall_winter_2009 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[28:30])
NRV_rainfall_winter_2010 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[31:33])
NRV_rainfall_winter_2011 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[34:36])
NRV_rainfall_winter_2012 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[37:39])
NRV_rainfall_winter_2013 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[40:42])
NRV_rainfall_winter_2014 <- sum(NRV_rainfall_winter_months$`Nedbør (mnd)`[43:45])

NRV_rainfall_winter_00_14 <- c(NRV_rainfall_winter_2000,NRV_rainfall_winter_2001,NRV_rainfall_winter_2002,NRV_rainfall_winter_2003,
                          NRV_rainfall_winter_2004,NRV_rainfall_winter_2005,NRV_rainfall_winter_2006,NRV_rainfall_winter_2007,
                          NRV_rainfall_winter_2008,NRV_rainfall_winter_2009,NRV_rainfall_winter_2010,NRV_rainfall_winter_2011,
                          NRV_rainfall_winter_2012,NRV_rainfall_winter_2013,NRV_rainfall_winter_2014)

#plot the rainfall in the winter months
plot(years[1:15], NRV_rainfall_winter_00_14, xlab = "winter",
    ylab = "rainfall (mm)", type = "histogram",  lwd = 3, main = "NRV")

#look at annual rainfall in Sjoa, representing NRV
NRV_rainfall_year <- read_excel("Sjoa_rainfall_year.xlsx")
NRV_rainfall_year <- na.omit(NRV_rainfall_year)
NRV_rainfall_year$Årsnedbør <- as.numeric(NRV_rainfall_year$Årsnedbør) #convert to numeric
NRV_rainfall_year$Year <- years[1:15]
plot(years, NRV_rainfall_year$Årsnedbør, xlab = "year", ylab = "rainfall (mm)",
    lwd = 3, type = "h", main = "NRV")
#fit a model for rainfall over year
NRV_rainfall_year$Num_year <- as.numeric(NRV_rainfall_year$Year)
NRV_rainfall_year_poly1 <- lm(Årsnedbør~Num_year, data = NRV_rainfall_year)
summary(NRV_rainfall_year_poly1)

#fit a Theil-Sen estimator
NRV_rainfall_year_poly1_TS <- mblm(Årsnedbør~Num_year, dataframe = NRV_rainfall_year, repeated = FALSE)
summary(NRV_rainfall_year_poly1_TS)

#----------------temperature------------------
#Now we want to look at temperature in Lillehammer, to represent this catchment
temp_data_day <- read_excel("Lillehammer_temp_day.xlsx")
#plot the temperature over time to get an overview of the data
temp_data_day <- na.omit(temp_data_day) #get rid of NA values
#fit a model for temperature against year

#plot summer months over the years
number_summer_days <- 91
summer_temp_2000 <- temp_data_day$`Middeltemperatur (døgn)`[153:(153+number_summer_days)]
summer_temp_2001 <- temp_data_day$`Middeltemperatur (døgn)`[518:(518+number_summer_days)]
summer_temp_2002 <- temp_data_day$`Middeltemperatur (døgn)`[883:(883+number_summer_days)]
summer_temp_2003 <- temp_data_day$`Middeltemperatur (døgn)`[1248:(1248+number_summer_days)]
summer_temp_2004 <- temp_data_day$`Middeltemperatur (døgn)`[1613:(1613+number_summer_days)]
summer_temp_2005 <- temp_data_day$`Middeltemperatur (døgn)`[1979:(1979+number_summer_days)]
summer_temp_2006 <- temp_data_day$`Middeltemperatur (døgn)`[2344:(2344+number_summer_days)]
summer_temp_2007 <- temp_data_day$`Middeltemperatur (døgn)`[2709:(2709+number_summer_days)]
summer_temp_2008 <- temp_data_day$`Middeltemperatur (døgn)`[3074:(3074+number_summer_days)]
summer_temp_2009 <- temp_data_day$`Middeltemperatur (døgn)`[3440:(3440+number_summer_days)]
summer_temp_2010 <- temp_data_day$`Middeltemperatur (døgn)`[3805:(3805+number_summer_days)]
```

```
summer_temp_2011 <- temp_data_day$`Middeltemperatur (døgn)`[4170:(4170+number_summer_days)]
summer_temp_2012 <- temp_data_day$`Middeltemperatur (døgn)`[4535:(4535+number_summer_days)]
summer_temp_2013 <- temp_data_day$`Middeltemperatur (døgn)`[4901:(4901+number_summer_days)]
summer_temp_2014 <- temp_data_day$`Middeltemperatur (døgn)`[5266:(5266+number_summer_days)]
#merge the lists
summer_temps_00_14 <- c(summer_temp_2000,summer_temp_2001,summer_temp_2002,summer_temp_2003,
                        summer_temp_2004,summer_temp_2005,summer_temp_2006,summer_temp_2007,
                        summer_temp_2008,summer_temp_2009,summer_temp_2010,summer_temp_2011,
                        summer_temp_2012,summer_temp_2013,summer_temp_2014)
#compute mean temperature of each summer
summer_mean_temps_00_14 = c(mean(summer_temp_2000),mean(summer_temp_2001),mean(summer_temp_2002),
                           mean(summer_temp_2003),mean(summer_temp_2004),mean(summer_temp_2005),
                           mean(summer_temp_2006),mean(summer_temp_2007),mean(summer_temp_2008),
                           mean(summer_temp_2009),mean(summer_temp_2010),mean(summer_temp_2011),
                           mean(summer_temp_2012),mean(summer_temp_2013),mean(summer_temp_2014))
#plot the temperature in the summer months
plot(years, summer_mean_temps_00_14, ylim = c(12,18), xlab = "summer",
     ylab = "mean summer temperature (°C)", type = "l", lwd = 2, main = "NRV")

#plot the mean summer temperature against year
plot(years[1:16], summer_mean_temp_00_15, xlab = "Summer", ylab = "Mean summer temperature (°C)",
     type = "l", ylim = c(12,18), lwd = 2, main = "NRV")
#fit a model of mean summer temperature against year
summer_mean_temp_year_poly1 <- lm(summer_mean_temp_00_15~years_list)
summary(summer_mean_temp_year_poly1)

#plot spring months over the years
number_spring_days <- 91
spring_temp_2000 <- temp_data_day$`Middeltemperatur (døgn)`[61:(61+number_spring_days)]
spring_temp_2001 <- temp_data_day$`Middeltemperatur (døgn)`[426:(426+number_spring_days)]
spring_temp_2002 <- temp_data_day$`Middeltemperatur (døgn)`[791:(791+number_spring_days)]
spring_temp_2003 <- temp_data_day$`Middeltemperatur (døgn)`[1156:(1156+number_spring_days)]
spring_temp_2004 <- temp_data_day$`Middeltemperatur (døgn)`[1521:(1521+number_spring_days)]
spring_temp_2005 <- temp_data_day$`Middeltemperatur (døgn)`[1887:(1887+number_spring_days)]
spring_temp_2006 <- temp_data_day$`Middeltemperatur (døgn)`[2252:(2252+number_spring_days)]
spring_temp_2007 <- temp_data_day$`Middeltemperatur (døgn)`[2617:(2617+number_spring_days)]
spring_temp_2008 <- temp_data_day$`Middeltemperatur (døgn)`[2982:(2982+number_spring_days)]
spring_temp_2009 <- temp_data_day$`Middeltemperatur (døgn)`[3348:(3348+number_spring_days)]
spring_temp_2010 <- temp_data_day$`Middeltemperatur (døgn)`[3713:(3713+number_spring_days)]
spring_temp_2011 <- temp_data_day$`Middeltemperatur (døgn)`[4078:(4078+number_spring_days)]
spring_temp_2012 <- temp_data_day$`Middeltemperatur (døgn)`[4443:(4443+number_spring_days)]
spring_temp_2013 <- temp_data_day$`Middeltemperatur (døgn)`[4809:(4809+number_spring_days)]
spring_temp_2014 <- temp_data_day$`Middeltemperatur (døgn)`[5174:(5174+number_spring_days)]
#merge the lists
spring_temps_00_14 <- c(spring_temp_2000,spring_temp_2001,spring_temp_2002,spring_temp_2003,
                        spring_temp_2004,spring_temp_2005,spring_temp_2006,spring_temp_2007,
                        spring_temp_2008,spring_temp_2009,spring_temp_2010,spring_temp_2011,
                        spring_temp_2012,spring_temp_2013,spring_temp_2014)
#plot the temperature in the spring months
plot(1:length(spring_temps_00_14), spring_temps_00_14, xlab = "spring days from 2000",
     ylab = "Temperature", type = "l")
#compute the mean temperature of each spring
spring_mean_temp_00_14 = c(mean(spring_temp_2000),mean(spring_temp_2001),mean(spring_temp_2002),
                           mean(spring_temp_2003),mean(spring_temp_2004),mean(spring_temp_2005),
                           mean(spring_temp_2006),mean(spring_temp_2007),mean(spring_temp_2008),
                           mean(spring_temp_2009),mean(spring_temp_2010),mean(spring_temp_2011),
                           mean(spring_temp_2012),mean(spring_temp_2013),mean(spring_temp_2014))
#plot the mean summer temperature against year
plot(years, spring_mean_temp_00_14, xlab = "spring", ylab = "mean spring temperature (°C)",
     type = "l", ylim = c(0,8), lwd = 2, main = "NRV")
#fit a model of mean summer temperature against year
summer_mean_temp_year_poly1 <- lm(summer_mean_temp_00_15~years_list)
summary(summer_mean_temp_year_poly1)

days_in_year <- 365.25
#checking whether the growing season is extended
get_growing_season <- function(temp_list, start_year, stop_year){
    days_growing_season <- c()
    for (year in start_year:stop_year){
        temp_year <- temp_list[grepl(as.character(year),temp_list$`Tid(norsk normaltid)`),]
        print(temp_year)
        temp_pre_summer_reversed <- temp_year[200:1,]
        print(temp_pre_summer_reversed)
        start_date <- which(temp_pre_summer_reversed$`Middeltemperatur (døgn)` <5)[1]
        temp_post_summer <- temp_year[200:days_in_year,]
        print("før sommer")
        print("etter sommer")
        stop_date <- which(temp_post_summer$`Middeltemperatur (døgn)`<5)[1]
        days <- stop_date+start_date-1
        days_growing_season <- c(days_growing_season, days)
    }
    return(days_growing_season)
}

NRV_growing_season <- get_growing_season(temp_data_day,2000,2014)
plot(years, NRV_growing_season, type = "l", lwd = 2, main = "NRV",
     xlab = "year", ylab = "days in growing season", ylim = c(100,200))

#Now we want to look at temperature in Lillehammer, to represent this catchment
temp_data_day <- read_excel("Lillehammer_temp_day.xlsx")
#plot the temperature over time to get an overview of the data
temp_data_day <- na.omit(temp_data_day) #get rid of NA values
plot(1:nrow(temp_data_day),temp_data_day$`Middeltemperatur (døgn)`, xlab = "Days from 1999",
     ylab = "Mean temperature of day", cex = 0.75, pch = 20)

#read in year temperature data from the excel file from Norsk klimaservicesenter
temp_data_year <- read_excel("Lillehammer_temp_year.xlsx")
temp_data_year <- na.omit(temp_data_year)
temp_data_year$Year <- years[1:15]
temp_data_year$Num_year <- as.numeric(temp_data_year$Year)
#fit a model for temperature against year
```

```
temp_year_poly1 <- lm(`Middeltemperatur (år)`~Num_year, data = temp_data_year)
summary(temp_year_poly1)



#--------------fit seasonal Kendall--------------
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "2. NRV Glomma")

#handling the data for date and color. Make a model for color vs date
NRV_water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
NRV_water_data <- na.omit(NRV_water_data) #get rid of the NA values
NRV_water_data <- NRV_water_data[51:nrow(NRV_water_data),] #go to year 2000
colnames(NRV_water_data) <- c("Date","Color")
NRV_water_data$Color <- as.numeric(NRV_water_data$Color) #make color data numeric
NRV_water_data <- NRV_water_data[order(NRV_water_data$Date),] #sort date in chronological order

#handling the data for date and color. Make a model for color vs date
NRV_water_data_TOC <- data.frame(water_data$Date, water_data$TOC, water_data$Color) #make a dataframe with only Date and Color
NRV_water_data_TOC <- na.omit(NRV_water_data_TOC) #get rid of the NA values
NRV_water_data_TOC <- NRV_water_data_TOC[20:nrow(NRV_water_data_TOC),]
colnames(NRV_water_data_TOC) <- c("Date","TOC","Color")
NRV_water_data_TOC$TOC <- as.numeric(NRV_water_data_TOC$TOC) #make TOC data numeric
NRV_water_data_TOC$Color <- as.numeric(NRV_water_data_TOC$Color) #make TOC data numeric
NRV_water_data_TOC <- NRV_water_data_TOC[order(NRV_water_data_TOC$Date),]

#see if data is normally distributed
hist(NRV_water_data$Color, breaks = seq(0,100,1))
NRV_water_data$Log_color <- log(NRV_water_data$Color)
hist(NRV_water_data$Log_color, breaks = seq(0,5,0.1))

#now we want to create a new column with year as a numeric variable
#create function for identifying the year in the date list
find_year <- function(date_list){
	year_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,1,4) #get the 4 first characters, which corresponds to year
		year_col <- append(year_col, date_string)
	}
	year_col <- as.numeric(year_col)
	return(year_col)
}

find_month <- function(date_list){
	month_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
		month_col <- append(month_col, date_string)
	}
	month_col <- as.numeric(month_col)
	return(month_col)
}

find_season <- function(date_list){
	season_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
		if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
			date_string <- 2
		}
		else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
			date_string <- 3
		}
		else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
			date_string <- 4
		}
		else {
			date_string <- 1
		}
		season_col <- append(season_col, date_string)
	}
	return(season_col)
}

change_december <- function(water_table){   #takes in the entire matrix
	index_of_december <- water_table$Month == 12
	print(index_of_december)
	water_table$Year[index_of_december] <- water_table$Year[index_of_december] + 1
	return(water_table)
}

NRV_year_col <- find_year(NRV_water_data$Date)
NRV_water_data$Year <- NRV_year_col

NRV_month_col <- find_month(NRV_water_data$Date)
NRV_water_data$Month <- NRV_month_col

NRV_season_col <- find_season(NRV_water_data$Date)
NRV_water_data$Season <- NRV_season_col
#handle December
NRV_water_data <- change_december(NRV_water_data)

#perform another seasonal Kendall test with 4 seasons with color
NRV_SK_rkt_1 <- rkt(date = NRV_water_data$Year, y = NRV_water_data$Color, block = NRV_water_data$Season, rep = "a")
#look at the model values
NRV_SK_rkt_1
NRV_SK_rkt_1$tau
NRV_SK_rkt_1$sl
```

```
#perform another seasonal Kendall test with 4 seasons with TOC
NRV_year_col <- find_year(NRV_water_data_TOC$Date)
NRV_water_data_TOC$Year <- NRV_year_col

NRV_month_col <- find_month(NRV_water_data_TOC$Date)
NRV_water_data_TOC$Month <- NRV_month_col

NRV_season_col <- find_season(NRV_water_data_TOC$Date)
NRV_water_data_TOC$Season <- NRV_season_col

#handle December
NRV_water_data_TOC <- change_december(NRV_water_data_TOC)

NRV_SK_rkt_2 <- rkt(date = NRV_water_data_TOC$Year, y = NRV_water_data_TOC$TOC, block = NRV_water_data_TOC$Season, rep = "a")
#look at the model values
NRV_SK_rkt_2
NRV_SK_rkt_2$tau
NRV_SK_rkt_2$sl

#perform another seasonal Kendall test with 4 seasons
NRV_SK_rkt_2 <- rkt(date = water_data$Year, y = water_data$Color, block = water_data$Month, rep = "a")
#look at the model values
NRV_SK_rkt_2
NRV_SK_rkt_2$tau
NRV_SK_rkt_2$sl

#fit a T-test adjusted for seasonality (TAS), linear regression with year and season as factors
NRV_TAS_1 <- lm(Color~ (Year) + as.factor(Season), data = water_data)
summary(NRV_TAS_1)

#plot colour against date
plot(NRV_water_data$Date, NRV_water_data$Color, xlab = "date", ylab = "colour (mg Pt/l)",
   cex = 0.75, pch = 20, main = "Glomma")

plot(NRV_water_data_TOC$Date, NRV_water_data_TOC$TOC, xlab = "date", ylab = "TOC (mg/L)",
   cex = 0.75, pch = 20, main = "Glomma")

#--------------rainfall------------
NRV_rainfall_months <- read_excel("Sjoa_rainfall.xlsx")
NRV_rainfall_months <- na.omit(NRV_rainfall_months)
NRV_rainfall_months$`Nedbør (mnd)` <- as.numeric(NRV_rainfall_months$`Nedbør (mnd)`)

#find season in NRV rainfall
find_rainfall_season <- function(date_list){
	season_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,1,2) #get the 4 first characters, which corresponds to year
		if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
			date_string <- 2
		}
		else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
			date_string <- 3
		}
		else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
			date_string <- 4
		}
		else {
			date_string <- 1
		}
		season_col <- append(season_col, date_string)
	}
	return(season_col)
}
find_rainfall_year <- function(date_list){
	year_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,4,7) #get the 4 first characters, which corresponds to year
		year_col <- append(year_col, date_string)
	}
	year_col <- as.numeric(year_col)
	return(year_col)
}

find_rainfall_month <- function(date_list){
	month_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,1,2) #get the 4 first characters, which corresponds to year
		month_col <- append(month_col, date_string)
	}
	month_col <- as.numeric(month_col)
	return(month_col)
}

NRV_rainfall_months$Season <- find_rainfall_season(NRV_rainfall_months$`Tid(norsk normaltid)`)
NRV_rainfall_months$Year <- find_rainfall_year(NRV_rainfall_months$`Tid(norsk normaltid)`)
NRV_rainfall_months$Month <- find_rainfall_month(NRV_rainfall_months$`Tid(norsk normaltid)`)

#make a function for making a rainfall column in the color matrix
NRV_rainfall_correlation <- function(color_table, rainfall_table){
	color_table$Rainfall <- seq(1,nrow(color_table),1)
	for (i in (1:nrow(color_table))){
		year <- color_table$Year[i]
		month <- color_table$Month[i]
		color_table$Rainfall[i] <- rainfall_table$`Nedbør (mnd)`[(rainfall_table$Year == year) & (rainfall_table$Month == month)]
	}
	return(color_table)
}
```

```
NRV_color_rainfall <- NRV_rainfall_correlation(NRV_water_data, NRV_rainfall_months)
#compute correlation between color and rainfall
cor(NRV_color_rainfall$Color, NRV_color_rainfall$Rainfall)
pcor.test(NRV_color_rainfall$Color, NRV_color_rainfall$Rainfall, NRV_color_rainfall$Month, method = "pearson")

#make correlations for the four different seasons
color_winter <- NRV_color_rainfall$Color[NRV_color_rainfall$Season == 1]
rainfall_winter <- NRV_color_rainfall$Rainfall[NRV_color_rainfall$Season == 1]
cor(color_winter, rainfall_winter)
plot(rainfall_winter, color_winter)

color_spring <- NRV_color_rainfall$Color[NRV_color_rainfall$Season == 2]
rainfall_spring <- NRV_color_rainfall$Rainfall[NRV_color_rainfall$Season == 2]
cor(color_spring, rainfall_spring)
plot(rainfall_spring, color_spring)

color_summer <- NRV_color_rainfall$Color[NRV_color_rainfall$Season == 3]
rainfall_summer <- NRV_color_rainfall$Rainfall[NRV_color_rainfall$Season == 3]
cor(color_summer, rainfall_summer)
plot(rainfall_summer, color_summer)

color_fall <- NRV_color_rainfall$Color[NRV_color_rainfall$Season == 4]
rainfall_fall <- NRV_color_rainfall$Rainfall[NRV_color_rainfall$Season == 4]
cor(color_fall, rainfall_fall)
plot(rainfall_fall, color_fall)

#fit linear model
NRV_color_rainfall_poly1 <- lm(Color~Rainfall,data = NRV_color_rainfall)
summary(NRV_color_rainfall_poly1)
plot(NRV_color_rainfall$Rainfall, NRV_color_rainfall$Color, xlab = "monthly rainfall (mm)", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Glomma")
lines(NRV_color_rainfall$Rainfall,NRV_color_rainfall_poly1$fitted.values)

#handle December
NRV_rainfall_months <- change_december(NRV_rainfall_months)

#fit SK model for rainfall
NRV_SK_rkt_rainfall <- rkt(date = NRV_rainfall_months$Year, y = NRV_rainfall_months$`Nedbør (mnd)`, block = NRV_rainfall_months$Season, rep = "a")
NRV_SK_rkt_rainfall

#fit TAS model for rainfall
NRV_TAS_rainfall <- lm(`Nedbør (mnd)`~ (Year) + as.factor(Season), data = NRV_rainfall_months)
summary(NRV_TAS_rainfall)

#fit SK and TAS models for temperature for NRV
NRV_temp_day <- read_excel("Lillehammer_temp_day.xlsx")
NRV_temp_day <- na.omit(NRV_temp_day)
#plot the temperature over time to get an overview of the data

find_temp_season <- function(date_list){
    season_col <- c()
    for (i in 1:length(date_list)){
        date_string <- as.character(date_list[i])
        date_string <- substr(date_string,4,5) #get the 4 first characters, which corresponds to year
        if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
            date_string <- 2
        }
        else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
            date_string <- 3
        }
        else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
            date_string <- 4
        }
        else {
            date_string <- 1
        }
        season_col <- append(season_col, date_string)
    }
    return(season_col)
}
find_temp_year <- function(date_list){
    year_col <- c()
    for (i in 1:length(date_list)){
        date_string <- as.character(date_list[i])
        date_string <- substr(date_string,7,10) #get the 4 first characters, which corresponds to year
        year_col <- append(year_col, date_string)
    }
    year_col <- as.numeric(year_col)
    return(year_col)
}

NRV_temperature_month_total <- function(matrix){
    list_month_total <- c()
    for (year in 2000:2014){
        for (month in 1:12){
            current_year_matrix <- matrix[matrix$Year == year,]
            actual_month <- current_year_matrix$`Middeltemperatur (døgn)`[current_year_matrix$Month == month]
            print(year)
            print(month)
            print(actual_month)
            month_total <- mean(actual_month)
            list_month_total <- append(list_month_total, month_total)
        }
    }
    return(list_month_total)
}

NRV_temp_day$Year <- find_temp_year(NRV_temp_day$`Tid(norsk normaltid)`)
NRV_temp_day$Season <- find_temp_season(NRV_temp_day$`Tid(norsk normaltid)`)
NRV_temp_day$Month <- find_temp_month(NRV_temp_day$`Tid(norsk normaltid)`)
```

```
#make a function for making a temperature column in the color matrix
NRV_temperature_correlation <- function(color_table, temperature_table){
	color_table$Temperature <- seq(1,nrow(color_table),1)
	color_table$Date <- as.character(color_table$Date)
	new_date_character <- str_split(color_table$Date,"-")
	for (i in (1:nrow(color_table))){
		year_character <- new_date_character[[i]][1]
		month_character <- new_date_character[[i]][2]
		day_character <- new_date_character[[i]][3]
		new_date_character[[i]] <- paste(day_character, month_character, year_character, sep = ".")
	}
	new_date_character <- unlist(new_date_character)
	for (i in (1:nrow(color_table)) ){
		color_table$Temperature[i] <- temperature_table$`Middeltemperatur (døgn)`[new_date_character[i] == temperature_table$`Tid(norsk normaltid)`]
	}
	return(color_table)
}

#make a function for making a temperature column in the color matrix
NRV_temperature_correlation <- function(color_table, temperature_table){
	color_table$Temperature <- seq(1,nrow(color_table),1)
	color_table$Date <- as.character(color_table$Date)
	new_date_character <- str_split(color_table$Date,"-")
	for (i in (1:nrow(color_table))){
		year_character <- new_date_character[[i]][1]
		month_character <- new_date_character[[i]][2]
		day_character <- new_date_character[[i]][3]
		new_date_character[[i]] <- paste(day_character, month_character, year_character, sep = ".")
	}
	new_date_character <- unlist(new_date_character)
	for (i in (2:nrow(color_table)) ){
		date_index <- match(new_date_character[i], temperature_table$`Tid(norsk normaltid)`)
		color_table$Temperature[i] <- mean(temperature_table$`Middeltemperatur (døgn)`[(date_index-6):date_index])
	}
	color_table$Temperature[1] <- mean(temperature_table$`Middeltemperatur (døgn)`[1:4])
	return(color_table)
}

NRV_color_temperature <- NRV_temperature_correlation(NRV_water_data, NRV_temp_day)
NRV_color_temperature$Rainfall <- NRV_color_rainfall$Rainfall
write_xlsx(NRV_color_temperature, "NRV_Date_Color_Temperature_Rainfall.xlsx")

#compute correlation between color and temperature
cor(NRV_color_temperature$Color, NRV_color_temperature$Temperature)
pcor.test(NRV_color_temperature$Color, NRV_color_temperature$Temperature, NRV_color_temperature$Month, method = "pearson")

#make correlations for the four different seasons
color_winter <- NRV_color_temperature$Color[NRV_color_temperature$Season == 1]
temperature_winter <- NRV_color_temperature$Temperature[NRV_color_temperature$Season == 1]
cor(color_winter, temperature_winter)
plot(temperature_winter, color_winter)

color_spring <- NRV_color_temperature$Color[NRV_color_temperature$Season == 2]
temperature_spring <- NRV_color_temperature$Temperature[NRV_color_temperature$Season == 2]
cor(color_spring, temperature_spring)
plot(temperature_spring, color_spring)

color_summer <- NRV_color_temperature$Color[NRV_color_temperature$Season == 3]
temperature_summer <- NRV_color_temperature$Temperature[NRV_color_temperature$Season == 3]
cor(color_summer, temperature_summer)
plot(temperature_summer, color_summer)

color_fall <- NRV_color_temperature$Color[NRV_color_temperature$Season == 4]
temperature_fall <- NRV_color_temperature$Temperature[NRV_color_temperature$Season == 4]
cor(color_fall, temperature_fall)
plot(temperature_fall, color_fall)

#fit linear model
NRV_color_temperature_poly1 <- lm(Color~Temperature,data = NRV_color_temperature2)
summary(NRV_color_temperature_poly1)
plot(NRV_color_temperature2$Temperature, NRV_color_temperature2$Color, xlab = "mean weekly temperature (°C)", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Glomma")
lines(NRV_color_temperature2$Temperature,NRV_color_temperature_poly1$fitted.values)

mean(NRV_color_rainfall$Rainfall[NRV_color_rainfall$Season == 1])
mean(NRV_color_rainfall$Rainfall[NRV_color_rainfall$Season == 2])
mean(NRV_color_rainfall$Rainfall[NRV_color_rainfall$Season == 3])
mean(NRV_color_rainfall$Rainfall[NRV_color_rainfall$Season == 4])

mean(NRV_color_temperature$Color[NRV_color_temperature$Season == 1])
mean(NRV_color_temperature$Color[NRV_color_temperature$Season == 2])
mean(NRV_color_temperature$Color[NRV_color_temperature$Season == 3])
mean(NRV_color_temperature$Color[NRV_color_temperature$Season == 4])

#handle December
NRV_temp_day <- change_december(NRV_temp_day)

NRV_temp_month <- NRV_temperature_month_total(NRV_temp_day)
#plot temperature against day on a monthly resolution
plot(as.POSIXct(months[1:180]), NRV_temp_month, xlab = "date (monthly)",
    ylab = "mean temperature (°C)", type = "l", main = "Lillehammer (Glomma)", col = "red", lwd = 2)

#look at growing season
NRV_growing_season <- get_growing_season(NRV_temp_day,2000,2014)
plot(seq(2000,2014,1), NRV_growing_season, type = "l", lwd = 2, main = "Glomma",
    xlab = "year", ylab = "days in growing season", ylim = c(100,200), xaxt = "n")
axis(1, at = seq(2000,2014,1))
NRV_growing_season_poly1 <- lm(NRV_growing_season~seq(2000,2014,1))
summary(NRV_growing_season_poly1)

NRV_growing_season_matrix <- data.frame(NRV_growing_season, seq(2000,2014,1))
```

```
colnames(NRV_growing_season_matrix) <- c("Days","Year")
NRV_growing_season_TS <- mblm(Days~Year, dataframe = NRV_growing_season_matrix, repeated = F)
summary(NRV_growing_season_TS)


#fit a  SK model for NRV temp
NRV_SK_rkt_temp <- rkt(date = NRV_temp_day$Year, y = NRV_temp_day$`Middeltemperatur (døgn)`, block = NRV_temp_day$Season, rep = "a")
NRV_SK_rkt_temp

#fit a TAS model for temperature
NRV_TAS_temp <- lm(`Middeltemperatur (døgn)`~ (Year) + as.factor(Season), data = NRV_temp_day)
summary(NRV_TAS_temp)

#fit TAS and SK model for NDVI
#fit SK model
NRV_SK_rkt_NDVI <- rkt(date = NRV_yearly_shape$year, y = NRV_yearly_shape$NDVI)
NRV_SK_rkt_NDVI

#test a Theil-Sen estimator
NRV_Mann_Kendall_rkt_NDVI <- mblm(NDVI~year, dataframe = NRV_yearly_shape, repeated = F)
summary(NRV_Mann_Kendall_rkt_NDVI) #different result than SK model

#fit linear model (because there is no seasonality)
NRV_TAS_temp <- lm(NRV_yearly_shape$NDVI~NRV_yearly_shape$year)
summary(NRV_TAS_temp)



#plot NDVI
#now we plot mean NDVI values for each year, as a function of year
plot(NRV_yearly_shape$year, NRV_yearly_shape$NDVI, type = "l", ylim = c(0.4,0.7),
    ylab = "NDVI", xlab = "year", cex = 0.75, pch = 20, lwd = 3, main = "Glomma", xaxt = "n")
axis(1, at = seq(1999,2014,1))
NRV_NDVI_shape_predictions_TS <- predict.lm(NRV_Mann_Kendall_rkt_NDVI)
lines(NRV_yearly_shape$year, NRV_NDVI_shape_predictions_TS, lwd = 3, col = "red")

#---------------acid deposition---------------
#fit Theil-Sen estimator for SO4
NRV_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = NRV_shape_SO4, repeated = FALSE)
summary(NRV_sulfate_year_poly1_TS)

NRV_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = NRV_shape_NO3, repeated = FALSE)
summary(NRV_nitrate_year_poly1_TS)

plot(NRV_shape_SO4$Year, NRV_shape_SO4$SO4, type = "l", col = "red", ylim = c(0,250),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Glomma", xaxt = "n")
par(new = T)
plot(NRV_shape_NO3$Year, NRV_shape_NO3$NO3, type = "l", col = "green", ylim = c(0,250),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Glomma", xaxt = "n")
legend(NRV_shape_SO4$Year[1], 50, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)
axis(1, at = seq(2000,2014,1))

predictions_sulfate_TS <- predict.lm(NRV_sulfate_year_poly1_TS)
lines(NRV_shape_SO4$Year, predictions_sulfate_TS, lwd = 3, col = "firebrick")
predictions_nitrate_TS <- predict.lm(NRV_nitrate_year_poly1_TS)
lines(NRV_shape_NO3$Year, predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#fit a linear model
NRV_sulfate_year_poly1 <- lm(NRV_shape_SO4$SO4~NRV_shape_SO4$Year)
summary(NRV_sulfate_year_poly1)

NRV_nitrate_year_poly1 <- lm(NRV_shape_NO3$NO3~NRV_shape_NO3$Year)
summary(NRV_nitrate_year_poly1)

predictions_sulfate <- predict.lm(NRV_sulfate_year_poly1)
lines(NRV_shape_SO4$Year, predictions_sulfate, lwd = 3, col = "firebrick")
predictions_nitrate <- predict.lm(NRV_nitrate_year_poly1)
lines(NRV_shape_NO3$Year, predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a mixed linear model of color as a function of SO4 and NO3

#look at correlation between SO4 and NO3
cor(NRV_shape_SO4$SO4, NRV_shape_NO3$NO3)

#first we have to collect the color into mean yearly values
Jordal_color_00_15 <- annual_color(water_data, 2000, 2015)
#add NO3 and SO4 to this model
Jordal_color_00_15$SO4 <- NRV_shape_SO4$SO4
Jordal_color_00_15$NO3 <- NRV_shape_NO3$NO3
colnames(Jordal_color_00_15) <- c("Year","Color","SO4","NO3")

Jordal_test <- data.frame(Jordal_color_00_15$SO4, Jordal_color_00_15$Color)
colnames(Jordal_test) <- c("SO4", "Color")

#fit a linear regression model with year as control variable
Jordal_color_SO4_NO3_year <- lm(Color~SO4+SO4*Year+NO3+NO3*Year,data = Jordal_color_00_15, scale = TRUE, center = TRUE)
summary(Jordal_color_SO4_NO3_year)

Jordal_color_SO4_NO3 <- lm(Color~SO4+NO3,data = Jordal_color_00_15, scale = TRUE, center = TRUE)
summary(Jordal_color_SO4_NO3)

calc.relimp(Jordal_color_SO4_NO3, type = c("lmg"), rela = TRUE)

#--------------PCA---------------
#gather the data for Jordal in one matrix
NRV_NDVI_shape <- read.csv("NRV_yearly_shape.csv")
NRV_NDVI_shape <- NRV_NDVI_shape[,-1]
NRV_yearly_shape <- annual_NDVI(NRV_NDVI_shape, 1999,2014)
#run functions in read_ndvi.R to produce NRV_shape_SO4

#define annual temperature and rainfall
```

```
NRV_rainfall_year <- read_excel("Sjoa_rainfall_year.xlsx")
NRV_rainfall_year <- na.omit(NRV_rainfall_year)
NRV_rainfall_year$Årsnedbør <- as.numeric(NRV_rainfall_year$Årsnedbør) #convert to numeric
NRV_rainfall_year$Year <- years[1:15]

NRV_temperature_year <- read_excel("Lillehammer_temp_year.xlsx")
NRV_temperature_year <- na.omit(NRV_temperature_year)
NRV_temperature_year$`Middeltemperatur (år)` <- as.numeric(NRV_temperature_year$`Middeltemperatur (år)`) #convert to numeric
NRV_temperature_year$Year <- years[1:15]

NRV_annual_color <- annual_color(NRV_water_data, 2000,2014)
NRV_annual_TOC <- annual_TOC(NRV_water_data_TOC, 2000,2014)

NRV_matrix <- data.frame(NRV_annual_color,NRV_rainfall_year$Årsnedbør,
                         NRV_temperature_year$`Middeltemperatur (år)`,
                         NRV_yearly_shape$NDVI[1:15], NRV_shape_SO4$SO4)
colnames(NRV_matrix) <- c("Year","Colour","Rainfall", "Temp", "NDVI", "SO4")
rownames <- seq(2000,2014,1)
rownames(NRV_matrix) <- as.character(rownames)

write_xlsx(NRV_matrix, "NRV_PCA_matrix.xlsx")

NRV_PCA <- prcomp(NRV_matrix[,-1], scale=TRUE)
NRV_PCA$rotation
autoplot(NRV_PCA, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Glomma", label = TRUE, label.size = 3, shape = F, scale = 0)
summary(NRV_PCA)
NRV_PCA$x

cor(NRV_matrix$Colour, NRV_matrix$Rainfall)
plot(NRV_matrix$Rainfall, NRV_matrix$Colour)

NRV_PCA_noyear <- prcomp(NRV_matrix[,-1], scale=TRUE)
NRV_PCA_noyear$rotation[,2]
autoplot(NRV_PCA_noyear, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Glomma", label = TRUE, label.size = 3, shape = F, scale = 0)
```

Port_Charlotte.R

```
#Analyzing data from Port Charlotte ----------------

library("readxl")
library("timetools")
library(dplyr)
library(ncdf4)
library(raster)
library(sf)
library(stringr)
library(rgdal)
library(mblm)
#read in the data
setwd("M:/Master thesis/Waterwork data/Scottish water")
water_data <- read_excel("Port Charlotte.xlsx", sheet = "Port Charlotte")

#handling the data for date and color. Make a model for color vs date
PCharlotte_water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
PCharlotte_water_data <- na.omit(PCharlotte_water_data) #get rid of the NA values
colnames(PCharlotte_water_data) <- c("Date","Color")
water_data$Color <- as.numeric(water_data$Color) #make color data numeric
PCharlotte_water_data <- PCharlotte_water_data[order(PCharlotte_water_data$Date),]

#fit a Theil-Sen estimator
PCharlotte_water_data$Num_date <- as.numeric(PCharlotte_water_data$Date) #add column with Num_date
PCharlotte_color_poly1_TS <- mblm(Color~Num_date, dataframe = PCharlotte_water_data, repeated = FALSE)
summary(PCharlotte_color_poly1_TS)
PCharlotte_color_predictions_TS <- predict.lm(object = PCharlotte_color_poly1_TS)
plot(PCharlotte_water_data$Date, PCharlotte_water_data$Color, xlab = "date", ylab = "colour (mg Pt/L)",
    cex = 0.75, pch = 20, main = "Port Charlotte")
lines(PCharlotte_water_data$Date, PCharlotte_color_predictions_TS, lwd = 3, col = "red")

#fit polynomial models of degree 1 on color vs days after January 1 2000
color_date_model <- lm(Color~Date, data = water_data)
summary(color_date_model)

predictions <- predict.lm(object = color_date_model)
#make scatter plot and plot of model
plot(water_data$Date, water_data$Color, xlab = "Date", ylab = "Color (mg Pt/l)", cex = 0.75, pch = 20)
lines(water_data$Date, predictions, col = "red", lwd = 3)

#handle rainfall
path <- setwd("M:/Master thesis/Waterwork data")
climate_data <- read_excel("Tiree_climate.xlsx")
#set up a matrix with PCharlotte climate data
PCharlotte_climate <- data.frame(climate_data$`Ballypatrick Forest`, climate_data$...4, climate_data$...5,
                                climate_data$`Dunstaffnage`, climate_data$...7, climate_data$...8,
                                climate_data$Tiree, climate_data$...13, climate_data$...14)
PCharlotte_climate <- PCharlotte_climate[2:nrow(PCharlotte_climate),] #drop the first row
PCharlotte_climate <- data.frame(mean(climate_data$`Ballypatrick Forest`,
        climate_data$`Dunstaffnage`, climate_data$`Tiree`), mean(climate_data$...4,
        climate_data$...7, climate_data$...10), mean(climate_data$...5,
        climate_data$...8), climate_data$...14)

colnames(PCharlotte_climate) <- c("max temp", "min temp", "rainfall")

#define years list in order to plot season rainfall data for each year later
years <- c("2000-01-01","2001-01-01","2002-01-01","2003-01-01",
          "2004-01-01","2005-01-01","2006-01-01","2007-01-01","2008-01-01",
          "2009-01-01","2010-01-01","2011-01-01","2012-01-01","2013-01-01",
          "2014-01-01","2015-01-01","2016-01-01")
years = as.POSIXct(years)

seconds_in_year <- 3600*24*365.25

#write temperatures and dates as numeric
PCharlotte_climate$`max temp` <- as.numeric(PCharlotte_climate$`max temp`)
PCharlotte_climate$`min temp` <- as.numeric(PCharlotte_climate$`min temp`)
PCharlotte_climate$rainfall <- as.numeric(PCharlotte_climate$rainfall)

#want to rewrite the dates to POSIXct format
x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=201), "%Y-%m-%d")
PCharlotte_climate$Date <- as.POSIXct(months) #convert dates to POSIXct format

#look at annual rainfall and temperature
PCharlotte_rainfall_2000 <- sum(PCharlotte_climate$rainfall[1:12])
PCharlotte_rainfall_2001 <- sum(PCharlotte_climate$rainfall[13:24])
PCharlotte_rainfall_2002 <- sum(PCharlotte_climate$rainfall[25:36])
PCharlotte_rainfall_2003 <- sum(PCharlotte_climate$rainfall[37:48])
PCharlotte_rainfall_2004 <- sum(PCharlotte_climate$rainfall[49:60])
PCharlotte_rainfall_2005 <- sum(PCharlotte_climate$rainfall[61:72])
PCharlotte_rainfall_2006 <- sum(PCharlotte_climate$rainfall[73:84])
PCharlotte_rainfall_2007 <- sum(PCharlotte_climate$rainfall[85:96])
PCharlotte_rainfall_2008 <- sum(PCharlotte_climate$rainfall[97:108])
PCharlotte_rainfall_2009 <- sum(PCharlotte_climate$rainfall[109:120])
PCharlotte_rainfall_2010 <- sum(PCharlotte_climate$rainfall[121:132])
PCharlotte_rainfall_2011 <- sum(PCharlotte_climate$rainfall[133:144])
PCharlotte_rainfall_2012 <- sum(PCharlotte_climate$rainfall[145:156])
PCharlotte_rainfall_2013 <- sum(PCharlotte_climate$rainfall[157:168])
PCharlotte_rainfall_2014 <- sum(PCharlotte_climate$rainfall[169:180])
PCharlotte_rainfall_2015 <- sum(PCharlotte_climate$rainfall[181:192])
PCharlotte_rainfall_00_15 <- c(PCharlotte_rainfall_2000,PCharlotte_rainfall_2001,PCharlotte_rainfall_2002,PCharlotte_rainfall_2003,
                            PCharlotte_rainfall_2004,PCharlotte_rainfall_2005,PCharlotte_rainfall_2006,PCharlotte_rainfall_2007,
                            PCharlotte_rainfall_2008,PCharlotte_rainfall_2009,PCharlotte_rainfall_2010,PCharlotte_rainfall_2011,
                            PCharlotte_rainfall_2012,PCharlotte_rainfall_2013,PCharlotte_rainfall_2014,PCharlotte_rainfall_2015)


#create a dataframe with rainfall and temperature of PCharlotte per year
PCharlotte_year <- data.frame(years[1:16], PCharlotte_rainfall_00_15,
```

```
                         PCharlotte_maxtemp_00_15, PCharlotte_mintemp_00_15)
colnames(PCharlotte_year) <- c("Year","Rainfall (mm)","Max temp (°C)", "Min temp (°C)")
PCharlotte_year$Num_year <- as.numeric(PCharlotte_year$Year)
PCharlotte_year$`Max temp (°C)` <- as.numeric(PCharlotte_year$`Max temp (°C)`)
PCharlotte_year$`Min temp (°C)` <- as.numeric(PCharlotte_year$`Min temp (°C)`)

#plot the rainfall for each year for PCharlotte
plot(years[1:16], PCharlotte_rainfall_00_15, ylim = c(50,2000), xlab = "year",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "PCharlotte")
#fit a linear model of rainfall as a function of year
PCharlotte_year_rainfall_poly1 <- lm(`Rainfall (mm)`~Year, data = PCharlotte_year)
summary(PCharlotte_year_rainfall_poly1)

#fit a Theil-Sen estimator of rainfall as a function of year
PCharlotte_year_rainfall_poly1_TS <- mblm(`Rainfall (mm)`~Num_year, data = PCharlotte_year)
summary(PCharlotte_year_rainfall_poly1_TS)
#compute yearly increase
coef(PCharlotte_year_rainfall_poly1_TS)[2]*seconds_in_year
PCharlotte_year_rainfall_TS_predictions <- predict.lm(object = PCharlotte_year_rainfall_poly1_TS)
plot(PCharlotte_year$Year, PCharlotte_year$`Rainfall (mm)`, xlab = "year",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "PCharlotte", ylim = c(50,2000))
lines(PCharlotte_year$Year, PCharlotte_year_rainfall_TS_predictions, col = "red", lwd = 3)

#plot temperature against year
plot(PCharlotte_year$Year, PCharlotte_year$`Max temp (°C)`, ylim = c(3,15), col = "red", xlab = "year",
    ylab = "max/min temperature (°C)", type = "l", lwd = 3, main = "Port Charlotte")
par(new = T)
#plot the min temperature in the summer months
plot(years[1:16], PCharlotte_year$`Min temp (°C)`, ylim = c(3,15), col = "blue", xlab = "year",
    ylab = "max/min temperature (°C)", type = "l", lwd = 3, main = "Port Charlotte")
legend(years[1],5, c("max temp","min temp"), col=c("red","blue"), cex = 0.55, lty = 1:1, lwd = 2)

#fit a model for max and min temperature as a function of year
PCharlotte_year_maxtemperature_poly1 <- lm(`Max temp (°C)`~Year, data = PCharlotte_year)
summary(PCharlotte_year_maxtemperature_poly1)
PCharlotte_year_mintemperature_poly1 <- lm(`Min temp (°C)`~Year, data = PCharlotte_year)
summary(PCharlotte_year_mintemperature_poly1)

#fit a Theil-Sen estimator for max and min temperature as a function of year
PCharlotte_year_maxtemperature_poly1_TS <- mblm(`Max temp (°C)`~Num_year, data = PCharlotte_year)
summary(PCharlotte_year_maxtemperature_poly1_TS)
coef(PCharlotte_year_maxtemperature_poly1_TS)[2]*seconds_in_year

PCharlotte_year_mintemperature_poly1_TS <- mblm(`Min temp (°C)`~Num_year, data = PCharlotte_year)
summary(PCharlotte_year_mintemperature_poly1_TS)
coef(PCharlotte_year_mintemperature_poly1_TS)[2]*seconds_in_year

#make predictions with the Theil-Sen estimators in order to plot the fitted lines
PCharlotte_maxtemperature_TS_predictions <- predict.lm(PCharlotte_year_maxtemperature_poly1_TS)
PCharlotte_mintemperature_TS_predictions <- predict.lm(PCharlotte_year_mintemperature_poly1_TS)
#plot temperature against year
plot(PCharlotte_year$Year, PCharlotte_year$`Max temp (°C)`, ylim = c(3,15), col = "red", xlab = "year",
    ylab = "max/min temperature (°C)", type = "l", lwd = 3, main = "Port Charlotte")
par(new = T)
#plot the min temperature in the summer months
plot(years[1:16], PCharlotte_year$`Min temp (°C)`, ylim = c(3,15), col = "blue", xlab = "year",
    ylab = "max/min temperature (°C)", type = "l", lwd = 3, main = "Port Charlotte")
legend(years[1],5, c("max temp","min temp"), col=c("red","blue"), cex = 0.55, lty = 1:1, lwd = 2)
lines(PCharlotte_year$Year, PCharlotte_maxtemperature_TS_predictions, col = "red", lwd = 3)
lines(PCharlotte_year$Year, PCharlotte_mintemperature_TS_predictions, col = "blue", lwd = 3)

#look at rainfall, plot rainfall against date
plot(PCharlotte_climate$Date, PCharlotte_climate$rainfall, cex = 0.75, pch = 20,
    type = "h", xlab = "date", ylab = "rainfall", main = "Port Charlotte")

#plot summer months over the years
June_indexes <- seq(6,198,12)
July_indexes <- seq(7,199,12)
August_indexes <- seq(8,200,12)
#merge the lists
summer_indexes <- c(June_indexes, July_indexes, August_indexes)
summer_indexes <- sort(summer_indexes)
#plot the rainfall in the summer months
plot(PCharlotte_climate$Date[summer_indexes], PCharlotte_climate$rainfall[summer_indexes], xlab = "Summer months",
    ylab = "Rainfall", type = "h")
#merge the rainfall of the summer months in one year to one variable
PCharlotte_rainfall_summer_months <- PCharlotte_climate[summer_indexes,]
PCharlotte_rainfall_summer_2000 <- sum(PCharlotte_rainfall_summer_months$rainfall[1:3])
PCharlotte_rainfall_summer_2001 <- sum(PCharlotte_rainfall_summer_months$rainfall[4:6])
PCharlotte_rainfall_summer_2002 <- sum(PCharlotte_rainfall_summer_months$rainfall[7:10])
PCharlotte_rainfall_summer_2003 <- sum(PCharlotte_rainfall_summer_months$rainfall[10:12])
PCharlotte_rainfall_summer_2004 <- sum(PCharlotte_rainfall_summer_months$rainfall[13:15])
PCharlotte_rainfall_summer_2005 <- sum(PCharlotte_rainfall_summer_months$rainfall[16:18])
PCharlotte_rainfall_summer_2006 <- sum(PCharlotte_rainfall_summer_months$rainfall[19:21])
PCharlotte_rainfall_summer_2007 <- sum(PCharlotte_rainfall_summer_months$rainfall[22:24])
PCharlotte_rainfall_summer_2008 <- sum(PCharlotte_rainfall_summer_months$rainfall[25:27])
PCharlotte_rainfall_summer_2009 <- sum(PCharlotte_rainfall_summer_months$rainfall[28:30])
PCharlotte_rainfall_summer_2010 <- sum(PCharlotte_rainfall_summer_months$rainfall[31:33])
PCharlotte_rainfall_summer_2011 <- sum(PCharlotte_rainfall_summer_months$rainfall[34:36])
PCharlotte_rainfall_summer_2012 <- sum(PCharlotte_rainfall_summer_months$rainfall[37:39])
PCharlotte_rainfall_summer_2013 <- sum(PCharlotte_rainfall_summer_months$rainfall[40:42])
PCharlotte_rainfall_summer_2014 <- sum(PCharlotte_rainfall_summer_months$rainfall[43:45])
PCharlotte_rainfall_summer_2015 <- sum(PCharlotte_rainfall_summer_months$rainfall[46:48])
PCharlotte_rainfall_summer_2016 <- sum(PCharlotte_rainfall_summer_months$rainfall[49:51])
PCharlotte_rainfall_summer_00_16 <- c(PCharlotte_rainfall_summer_2000,PCharlotte_rainfall_summer_2001,PCharlotte_rainfall_summer_2002,PCharlotte_rainfall_summer_2003,
                              PCharlotte_rainfall_summer_2004,PCharlotte_rainfall_summer_2005,PCharlotte_rainfall_summer_2006,PCharlotte_rainfall_summer_2007,
                              PCharlotte_rainfall_summer_2008,PCharlotte_rainfall_summer_2009,PCharlotte_rainfall_summer_2010,PCharlotte_rainfall_summer_2011,
                              PCharlotte_rainfall_summer_2012,PCharlotte_rainfall_summer_2013,PCharlotte_rainfall_summer_2014,PCharlotte_rainfall_summer_2015,
                              PCharlotte_rainfall_summer_2016)
#plot the temperature in the summer months
plot(years[1:17], PCharlotte_rainfall_summer_00_16, xlab = "summer",
```

```
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Port Charlotte")

#plot spring months over the years
March_indexes <- seq(3,195,12)
April_indexes <- seq(4,196,12)
May_indexes <- seq(5,197,12)
#merge the lists
spring_indexes <- c(March_indexes, April_indexes, May_indexes)
spring_indexes <- sort(spring_indexes)

plot(PCharlotte_climate$Date[spring_indexes], PCharlotte_climate$rainfall[spring_indexes], xlab = "spring months",
    ylab = "rainfall (mm)", type = "h")

#merge the rainfall of the spring months in one year to one variable
PCharlotte_rainfall_spring_months <- PCharlotte_climate[spring_indexes,]
PCharlotte_rainfall_spring_2000 <- sum(PCharlotte_rainfall_spring_months$rainfall[1:3])
PCharlotte_rainfall_spring_2001 <- sum(PCharlotte_rainfall_spring_months$rainfall[4:6])
PCharlotte_rainfall_spring_2002 <- sum(PCharlotte_rainfall_spring_months$rainfall[7:10])
PCharlotte_rainfall_spring_2003 <- sum(PCharlotte_rainfall_spring_months$rainfall[10:12])
PCharlotte_rainfall_spring_2004 <- sum(PCharlotte_rainfall_spring_months$rainfall[13:15])
PCharlotte_rainfall_spring_2005 <- sum(PCharlotte_rainfall_spring_months$rainfall[16:18])
PCharlotte_rainfall_spring_2006 <- sum(PCharlotte_rainfall_spring_months$rainfall[19:21])
PCharlotte_rainfall_spring_2007 <- sum(PCharlotte_rainfall_spring_months$rainfall[22:24])
PCharlotte_rainfall_spring_2008 <- sum(PCharlotte_rainfall_spring_months$rainfall[25:27])
PCharlotte_rainfall_spring_2009 <- sum(PCharlotte_rainfall_spring_months$rainfall[28:30])
PCharlotte_rainfall_spring_2010 <- sum(PCharlotte_rainfall_spring_months$rainfall[31:33])
PCharlotte_rainfall_spring_2011 <- sum(PCharlotte_rainfall_spring_months$rainfall[34:36])
PCharlotte_rainfall_spring_2012 <- sum(PCharlotte_rainfall_spring_months$rainfall[37:39])
PCharlotte_rainfall_spring_2013 <- sum(PCharlotte_rainfall_spring_months$rainfall[40:42])
PCharlotte_rainfall_spring_2014 <- sum(PCharlotte_rainfall_spring_months$rainfall[43:45])
PCharlotte_rainfall_spring_2015 <- sum(PCharlotte_rainfall_spring_months$rainfall[46:48])
PCharlotte_rainfall_spring_2016 <- sum(PCharlotte_rainfall_spring_months$rainfall[49:51])
PCharlotte_rainfall_spring_00_16 <- c(PCharlotte_rainfall_spring_2000,PCharlotte_rainfall_spring_2001,PCharlotte_rainfall_spring_2002,PCharlotte_rainfall_spring_2003,
                              PCharlotte_rainfall_spring_2004,PCharlotte_rainfall_spring_2005,PCharlotte_rainfall_spring_2006,PCharlotte_rainfall_spring_2007,
                              PCharlotte_rainfall_spring_2008,PCharlotte_rainfall_spring_2009,PCharlotte_rainfall_spring_2010,PCharlotte_rainfall_spring_2011,
                              PCharlotte_rainfall_spring_2012,PCharlotte_rainfall_spring_2013,PCharlotte_rainfall_spring_2014,PCharlotte_rainfall_spring_2015,
                              PCharlotte_rainfall_spring_2016)

#plot the temperature in the spring months
plot(years[1:17], PCharlotte_rainfall_spring_00_16, xlab = "spring",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Port Charlotte")

Sept_indexes <- seq(9,189,12)
Oct_indexes <- seq(10,190,12)
Nov_indexes <- seq(11,191,12)
#merge the lists
fall_indexes <- c(Sept_indexes, Oct_indexes, Nov_indexes)
fall_indexes <- sort(fall_indexes)

plot(PCharlotte_climate$Date[fall_indexes], PCharlotte_climate$rainfall[fall_indexes], xlab = "fall months",
    ylab = "rainfall (mm)", type = "h")

#merge the rainfall of the fall months in one year to one variable
PCharlotte_rainfall_fall_months <- PCharlotte_climate[fall_indexes,]
PCharlotte_rainfall_fall_2000 <- sum(PCharlotte_rainfall_fall_months$rainfall[1:3])
PCharlotte_rainfall_fall_2001 <- sum(PCharlotte_rainfall_fall_months$rainfall[4:6])
PCharlotte_rainfall_fall_2002 <- sum(PCharlotte_rainfall_fall_months$rainfall[7:10])
PCharlotte_rainfall_fall_2003 <- sum(PCharlotte_rainfall_fall_months$rainfall[10:12])
PCharlotte_rainfall_fall_2004 <- sum(PCharlotte_rainfall_fall_months$rainfall[13:15])
PCharlotte_rainfall_fall_2005 <- sum(PCharlotte_rainfall_fall_months$rainfall[16:18])
PCharlotte_rainfall_fall_2006 <- sum(PCharlotte_rainfall_fall_months$rainfall[19:21])
PCharlotte_rainfall_fall_2007 <- sum(PCharlotte_rainfall_fall_months$rainfall[22:24])
PCharlotte_rainfall_fall_2008 <- sum(PCharlotte_rainfall_fall_months$rainfall[25:27])
PCharlotte_rainfall_fall_2009 <- sum(PCharlotte_rainfall_fall_months$rainfall[28:30])
PCharlotte_rainfall_fall_2010 <- sum(PCharlotte_rainfall_fall_months$rainfall[31:33])
PCharlotte_rainfall_fall_2011 <- sum(PCharlotte_rainfall_fall_months$rainfall[34:36])
PCharlotte_rainfall_fall_2012 <- sum(PCharlotte_rainfall_fall_months$rainfall[37:39])
PCharlotte_rainfall_fall_2013 <- sum(PCharlotte_rainfall_fall_months$rainfall[40:42])
PCharlotte_rainfall_fall_2014 <- sum(PCharlotte_rainfall_fall_months$rainfall[43:45])
PCharlotte_rainfall_fall_2015 <- sum(PCharlotte_rainfall_fall_months$rainfall[46:48])
PCharlotte_rainfall_fall_00_15 <- c(PCharlotte_rainfall_fall_2000,PCharlotte_rainfall_fall_2001,PCharlotte_rainfall_fall_2002,PCharlotte_rainfall_fall_2003,
                             PCharlotte_rainfall_fall_2004,PCharlotte_rainfall_fall_2005,PCharlotte_rainfall_fall_2006,PCharlotte_rainfall_fall_2007,
                             PCharlotte_rainfall_fall_2008,PCharlotte_rainfall_fall_2009,PCharlotte_rainfall_fall_2010,PCharlotte_rainfall_fall_2011,
                             PCharlotte_rainfall_fall_2012,PCharlotte_rainfall_fall_2013,PCharlotte_rainfall_fall_2014,PCharlotte_rainfall_fall_2015)

#plot the temperature in the spring months
plot(years[1:16], PCharlotte_rainfall_fall_00_15, xlab = "fall",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Port Charlotte")

#-----------------look at temperature---------------
#plot max and min temperature as a function of date
plot(PCharlotte_climate$Date, PCharlotte_climate$`max temp`, cex = 0.75, pch = 20, ylim = c(0,20),
    type = "l", xlab = "date", ylab = "temperature (°C)", main = "Port Charlotte", col = "red")
par(new = T)
plot(PCharlotte_climate$Date, PCharlotte_climate$`min temp`, cex = 0.75, pch = 20, ylim = c(0,20),
    type = "l", xlab = "date", ylab = "temperature (°C)", main = "Port Charlotte", col = "green")


#-----------------fit Seasonal Kendall for Port Charlotte----------

setwd("M:/Master thesis/Waterwork data/Scottish water")
water_data <- read_excel("Port Charlotte.xlsx", sheet = "Port Charlotte")

#handling the data for date and color. Make a model for color vs date
PCharlotte_water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
PCharlotte_water_data <- na.omit(PCharlotte_water_data) #get rid of the NA values
PCharlotte_water_data <- PCharlotte_water_data[51:nrow(PCharlotte_water_data),] #go to year 2000
colnames(PCharlotte_water_data) <- c("Date","Color")
PCharlotte_water_data$Color <- as.numeric(PCharlotte_water_data$Color) #make color data numeric
PCharlotte_water_data <- PCharlotte_water_data[order(PCharlotte_water_data$Date),] #sort date in chronological order
```

```
#see if data is normally distributed
hist(PCharlotte_water_data$Color, breaks = seq(0,300,10))
PCharlotte_water_data$Log_color <- log(PCharlotte_water_data$Color)
hist(PCharlotte_water_data$Log_color, breaks = seq(0,7,0.1))

#now we want to create a new column with year as a numeric variable
#create function for identifying the year in the date list
find_year <- function(date_list){
	year_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,1,4) #get the 4 first characters, which corresponds to year
		year_col <- append(year_col, date_string)
	}
	year_col <- as.numeric(year_col)
	return(year_col)
}

find_month <- function(date_list){
	month_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
		month_col <- append(month_col, date_string)
	}
	month_col <- as.numeric(month_col)
	return(month_col)
}

find_season <- function(date_list){
	season_col <- c()
	for (i in 1:length(date_list)){
		date_string <- as.character(date_list[i])
		date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
		if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
			date_string <- 2
		}
		else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
			date_string <- 3
		}
		else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
			date_string <- 4
		}
		else {
			date_string <- 1
		}
		season_col <- append(season_col, date_string)
	}
	return(season_col)
}

PCharlotte_year_col <- find_year(PCharlotte_water_data$Date)
PCharlotte_water_data$Year <- PCharlotte_year_col

PCharlotte_month_col <- find_month(PCharlotte_water_data$Date)
PCharlotte_water_data$Month <- PCharlotte_month_col

PCharlotte_season_col <- find_season(PCharlotte_water_data$Date)
PCharlotte_water_data$Season <- PCharlotte_season_col

#function for changing December months to be associated with January/February the year after
change_december <- function(water_table){   #takes in the entire matrix
	index_of_december <- water_table$Month == 12
	print(index_of_december)
	water_table$Year[index_of_december] <- water_table$Year[index_of_december] + 1
	return(water_table)
}
PCharlotte_water_data <- change_december(PCharlotte_water_data)

#perform another seasonal Kendall test with 4 seasons with color
PCharlotte_SK_rkt_1 <- rkt(date = PCharlotte_water_data$Year, y = PCharlotte_water_data$Color, block = PCharlotte_water_data$Season, rep = "a")
#look at the model values
PCharlotte_SK_rkt_1
PCharlotte_SK_rkt_1$tau
PCharlotte_SK_rkt_1$sl

#perform another seasonal Kendall test with 4 seasons
PCharlotte_SK_rkt_2 <- rkt(date = water_data$Year, y = water_data$Color, block = water_data$Month, rep = "a")
#look at the model values
PCharlotte_SK_rkt_2
PCharlotte_SK_rkt_2$tau
PCharlotte_SK_rkt_2$sl

#fit a T-test adjusted for seasonality (TAS), linear regression with year and season as factors
PCharlotte_TAS_1 <- lm(Color~ (Year) + as.factor(Season), data = water_data)
summary(PCharlotte_TAS_1)

#--------------rainfall------------
path <- setwd("M:/Master thesis/Waterwork data")
climate_data <- read_excel("Tiree_climate.xlsx", col_names = FALSE)
PCharlotte_rainfall_months <- data.frame(climate_data$...1, climate_data$...2, climate_data$...3,
                                         climate_data$...4, climate_data$...6)
PCharlotte_rainfall_months <- na.omit(PCharlotte_rainfall_months)
PCharlotte_rainfall_months <- PCharlotte_rainfall_months[1:192,]
colnames(PCharlotte_rainfall_months) <- c("Year","Month","T_max","T_min","Rainfall")
PCharlotte_rainfall_months$T_max <- as.numeric(PCharlotte_rainfall_months$T_max)
PCharlotte_rainfall_months$T_min <- as.numeric(PCharlotte_rainfall_months$T_min)
PCharlotte_rainfall_months$Rainfall <- as.numeric(PCharlotte_rainfall_months$Rainfall)
cor(PCharlotte_rainfall_months$T_max, PCharlotte_rainfall_months$T_min, use = "complete.obs")
PCharlotte_temperature_months <- PCharlotte_rainfall_months[,-5]
```

```
#find season in PCharlotte rainfall
find_rainfall_season <- function(date_list) {
    season_col <- c()
    for (i in 1:length(date_list)) {
        if (date_list[i] > 2 && date_list[i] < 6 ){
        season <- 2
        }
        else if (date_list[i] > 5 && date_list[i] < 9 ){
            season <- 3
        }
        else if (date_list[i] > 8 && date_list[i] < 12 ){
            season <- 4
        }
        else {
            season <- 1
        }
        season_col <- append(season_col, season)
    }
    return(season_col)
}
find_rainfall_year <- function(date_list){
    year_col <- c()
    for (i in 1:length(date_list)){
        date_string <- as.character(date_list[i])
        date_string <- substr(date_string,4,7) #get the 4 first characters, which corresponds to year
        year_col <- append(year_col, date_string)
    }
    year_col <- as.numeric(year_col)
    return(year_col)
}

PCharlotte_rainfall_months$Season <- find_rainfall_season(PCharlotte_rainfall_months$Month)

#make a function for making a rainfall column in the color matrix
PCharlotte_rainfall_correlation <- function(color_table, rainfall_table){
    color_table$Rainfall <- seq(1,nrow(color_table),1)
    for (i in (1:nrow(color_table))){
        year <- color_table$Year[i]
        month <- color_table$Month[i]
        color_table$Rainfall[i] <- rainfall_table$Rainfall[(rainfall_table$Year == year) & (rainfall_table$Month == month)]
    }
    return(color_table)
}
PCharlotte_color_rainfall <- PCharlotte_rainfall_correlation(PCharlotte_water_data, PCharlotte_rainfall_months)
PCharlotte_color_rainfall <- na.omit(PCharlotte_color_rainfall)
#compute correlation between color and rainfall
cor(PCharlotte_color_rainfall$Color, PCharlotte_color_rainfall$Rainfall, use = "complete.obs")
#fit linear model

#make correlations for the four different seasons
color_winter <- PCharlotte_color_rainfall$Color[PCharlotte_color_rainfall$Season == 1]
rainfall_winter <- PCharlotte_color_rainfall$Rainfall[PCharlotte_color_rainfall$Season == 1]
cor(color_winter, rainfall_winter, use = "complete.obs")
plot(rainfall_winter, color_winter)

color_spring <- PCharlotte_color_rainfall$Color[PCharlotte_color_rainfall$Season == 2]
rainfall_spring <- PCharlotte_color_rainfall$Rainfall[PCharlotte_color_rainfall$Season == 2]
cor(color_spring, rainfall_spring, use = "complete.obs")
plot(rainfall_spring, color_spring)

color_summer <- PCharlotte_color_rainfall$Color[PCharlotte_color_rainfall$Season == 3]
rainfall_summer <- PCharlotte_color_rainfall$Rainfall[PCharlotte_color_rainfall$Season == 3]
cor(color_summer, rainfall_summer, use = "complete.obs")
plot(rainfall_summer, color_summer)

color_fall <- PCharlotte_color_rainfall$Color[PCharlotte_color_rainfall$Season == 4]
rainfall_fall <- PCharlotte_color_rainfall$Rainfall[PCharlotte_color_rainfall$Season == 4]
cor(color_fall, rainfall_fall, use = "complete.obs")
plot(rainfall_fall, color_fall)

PCharlotte_color_rainfall_poly1 <- lm(Color~Rainfall,data = PCharlotte_color_rainfall)
summary(PCharlotte_color_rainfall_poly1)
plot(PCharlotte_color_rainfall$Rainfall, PCharlotte_color_rainfall$Color,  xlab = "monthly rainfall (mm)", ylab = "colour (mg Pt/l)",
   cex = 0.75, pch = 20, main = "Port Charlotte")
lines(PCharlotte_color_rainfall$Rainfall,PCharlotte_color_rainfall_poly1$fitted.values, col = "red", lwd = 3)

#correlation between color and temperature
PCharlotte_temperature_correlation <- function(color_table, temperature_table){
    color_table$Temperature <- seq(1,nrow(color_table),1)
    for (i in (1:nrow(color_table))){
        year <- color_table$Year[i]
        month <- color_table$Month[i]
        color_table$Temperature[i] <- temperature_table$T_max[(temperature_table$Year == year) & (temperature_table$Month == month)]
    }
    return(color_table)
}
PCharlotte_color_temperature <- PCharlotte_temperature_correlation(PCharlotte_water_data, PCharlotte_rainfall_months)
PCharlotte_color_temperature <- na.omit(PCharlotte_color_temperature)
#combine the temperature and rainfall into one column
PCharlotte_color_temperature$Rainfall <- PCharlotte_color_rainfall$Rainfall
PCharlotte_color_temperature_rainfall <- PCharlotte_color_temperature[,-3:(-5)]
#write the data to file
write_xlsx(PCharlotte_color_temperature_rainfall, "PCharlotte_Date_Color_Temperature_Rainfall.xlsx")

PCharlotte_color_rainfall$Temperature <- PCharlotte_color_temperature$Temperature

#compute correlation between color and temperature
cor(PCharlotte_color_temperature$Color, PCharlotte_color_temperature$Temperature)
mean(PCharlotte_color_temperature$Color[PCharlotte_color_temperature$Season == 1])
mean(PCharlotte_color_temperature$Color[PCharlotte_color_temperature$Season == 2])
mean(PCharlotte_color_temperature$Color[PCharlotte_color_temperature$Season == 3])
```

```
mean(PCharlotte_color_temperature$Color[PCharlotte_color_temperature$Season == 4])

#compute correlation between color and temperature
cor(Jordal_color_temperature$Color, Jordal_color_temperature$Temperature)
pcor.test(Jordal_color_temperature$Color, Jordal_color_temperature$Temperature, as.factor(Jordal_color_temperature$Month), method = "pearson")
plot(Jordal_color_temperature$Temperature, Jordal_color_temperature$Color)

#make correlations for the four different seasons
color_winter <- PCharlotte_color_temperature$Color[PCharlotte_color_temperature$Season == 1]
temperature_winter <- PCharlotte_color_temperature$Temperature[PCharlotte_color_temperature$Season == 1]
cor(color_winter, temperature_winter, use = "complete.obs")
plot(temperature_winter, color_winter)

color_spring <- PCharlotte_color_temperature$Color[PCharlotte_color_temperature$Season == 2]
temperature_spring <- PCharlotte_color_temperature$Temperature[PCharlotte_color_temperature$Season == 2]
cor(color_spring, temperature_spring, use = "complete.obs")
plot(temperature_spring, color_spring)

color_summer <- PCharlotte_color_temperature$Color[PCharlotte_color_temperature$Season == 3]
temperature_summer <- PCharlotte_color_temperature$Temperature[PCharlotte_color_temperature$Season == 3]
cor(color_summer, temperature_summer, use = "complete.obs")
plot(temperature_summer, color_summer)

color_fall <- PCharlotte_color_temperature$Color[PCharlotte_color_temperature$Season == 4]
temperature_fall <- PCharlotte_color_temperature$Temperature[PCharlotte_color_temperature$Season == 4]
cor(color_fall, temperature_fall, use = "complete.obs")
plot(temperature_fall, color_fall)

#fit linear model
PCharlotte_color_temperature_poly1 <- lm(Color~Temperature,data = PCharlotte_color_temperature)
summary(PCharlotte_color_temperature_poly1)
plot(PCharlotte_color_temperature$Temperature, PCharlotte_color_temperature$Color, xlab = "mean monthly temperature (°C)", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Port Charlotte")
lines(PCharlotte_color_temperature$Temperature,PCharlotte_color_temperature_poly1$fitted.values, col = "red", lwd = 3)

PCharlotte_rainfall_months <- change_december(PCharlotte_rainfall_months)

#fit SK model for rainfall
PCharlotte_SK_rkt_rainfall <- rkt(date = PCharlotte_rainfall_months$Year, y = PCharlotte_rainfall_months$Rainfall, block = PCharlotte_rainfall_months$Season, rep = "a")
PCharlotte_SK_rkt_rainfall

#plot rainfall against date
x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=192), "%Y-%m-%d")
PCharlotte_rainfall_months$Months <- as.POSIXct(months)
plot(PCharlotte_rainfall_months$Months, PCharlotte_rainfall_months$Rainfall, xlab = "date (monthly)",
    ylab = "rainfall (mm)", type = "h", main = "Tiree (Port Charlotte)", col = "blue")
#make predictions manually
intercept_list <- PCharlotte_rainfall_months$Rainfall- PCharlotte_SK_rkt_rainfall$B*(PCharlotte_rainfall_months$Year-2000)
intercept <- median(intercept_list, na.rm = TRUE)
PCharlotte_SK_predictions <- intercept + PCharlotte_SK_rkt_rainfall$B*seq(0,16,1)
lines(years[1:17], PCharlotte_SK_predictions, col = "red", lwd = 3)

#fit a  SK model for NRV temp
PCharlotte_SK_rkt_temp_max <- rkt(date = PCharlotte_rainfall_months$Year, y = PCharlotte_rainfall_months$T_max, block = PCharlotte_rainfall_months$Season, rep = "a")
PCharlotte_SK_rkt_temp_max

PCharlotte_SK_rkt_temp_min <- rkt(date = PCharlotte_rainfall_months$Year, y = PCharlotte_rainfall_months$T_min, block = PCharlotte_rainfall_months$Season, rep = "a")
PCharlotte_SK_rkt_temp_min

#plot temperature against date with monthly resolution
plot(PCharlotte_rainfall_months$Months, PCharlotte_rainfall_months$T_max, xlab = "date (monthly)",
    ylab = "max/min temperature (°C)", type = "l", main = "Tiree (Port Charlotte)", col = "red", lwd = 2, ylim = c(-4,20))
par(new = T)
plot(PCharlotte_rainfall_months$Months, PCharlotte_rainfall_months$T_min, xlab = "date (monthly)",
    ylab = "max/min temperature (°C)", type = "l", main = "Tiree (Port Charlotte)", col = "blue", lwd = 2, ylim = c(-4,20))
legend(PCharlotte_rainfall_months$Months[1], 0, c("max temp","min temp"), col=c("red","blue"), cex = 0.75, lty = 1:1, lwd = 2)

#fit a TAS model for temperature
PCharlotte_TAS_temp <- lm(`Middeltemperatur (døgn)`~ (Year) + as.factor(Season), data = PCharlotte_temp_day)
summary(PCharlotte_TAS_temp)

#fit TAS and SK model for NDVI
#fit SK model
PCharlotte_SK_rkt_NDVI <- rkt(date = PCharlotte_yearly_shape$year, y = PCharlotte_yearly_shape$NDVI)
PCharlotte_SK_rkt_NDVI

#test a Theil-Sen estimator
PCharlotte_Mann_Kendall_rkt_NDVI <- mblm(NDVI~year, dataframe = PCharlotte_yearly, repeated = F)
summary(PCharlotte_Mann_Kendall_rkt_NDVI) #different result than SK model

#fit linear model (because there is no seasonality)
PCharlotte_TAS_temp <- lm(PCharlotte_yearly$NDVI~PCharlotte_yearly$year)
summary(PCharlotte_TAS_temp)

#plot NDVI
#now we plot mean NDVI values for each year, as a function of year
plot(PCharlotte_yearly$year, PCharlotte_yearly$NDVI, type = "l", ylim = c(0.5,0.8),
    ylab = "NDVI", xlab = "year", cex = 0.75, pch = 20, lwd = 3, main = "Port Charlotte", xaxt = "n")
axis(1, at = seq(1999,2015,1))
PCharlotte_NDVI_shape_predictions_TS <- predict.lm(PCharlotte_Mann_Kendall_rkt_NDVI)
lines(PCharlotte_yearly$year, PCharlotte_NDVI_shape_predictions_TS, lwd = 3, col = "red")

#---------------acid deposition---------------
#fit Theil-Sen estimator for SO4
PCharlotte_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = PCharlotte_acid, repeated = FALSE)
summary(PCharlotte_sulfate_year_poly1_TS)

PCharlotte_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = PCharlotte_acid, repeated = FALSE)
summary(PCharlotte_nitrate_year_poly1_TS)
```

```
plot(PCharlotte_acid$Year, PCharlotte_acid$SO4, type = "l", col = "red", ylim = c(0,500),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Port Charlotte", xaxt = "n")
par(new = T)
plot(PCharlotte_acid$Year, PCharlotte_acid$NO3, type = "l", col = "green", ylim = c(0,500),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Port Charlotte", xaxt = "n")
legend(PCharlotte_acid$Year[1], 120, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)
axis(1, at = seq(2000,2015,1))

predictions_sulfate_TS <- predict.lm(PCharlotte_sulfate_year_poly1_TS)
lines(PCharlotte_acid$Year, predictions_sulfate_TS, lwd = 3, col = "firebrick")
predictions_nitrate_TS <- predict.lm(PCharlotte_nitrate_year_poly1_TS)
lines(PCharlotte_acid$Year, predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#fit a linear model
PCharlotte_sulfate_year_poly1 <- lm(PCharlotte_acid$SO4~PCharlotte_acid$Year)
summary(PCharlotte_sulfate_year_poly1)

PCharlotte_nitrate_year_poly1 <- lm(PCharlotte_acid$NO3~PCharlotte_acid$Year)
summary(PCharlotte_nitrate_year_poly1)

predictions_sulfate <- predict.lm(PCharlotte_sulfate_year_poly1)
lines(PCharlotte_shape_SO4$Year, predictions_sulfate, lwd = 3, col = "firebrick")
predictions_nitrate <- predict.lm(PCharlotte_nitrate_year_poly1)
lines(PCharlotte_shape_NO3$Year, predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a mixed linear model of color as a function of SO4 and NO3

cor(PCharlotte_acid$SO4, PCharlotte_acid$NO3)

#first we have to collect the color into mean yearly values
PCharlotte_color_00_15 <- annual_color(water_data, 2000, 2015)
#add NO3 and SO4 to this model
PCharlotte_color_00_15$SO4 <- PCharlotte_shape_SO4$SO4
PCharlotte_color_00_15$NO3 <- PCharlotte_shape_NO3$NO3
colnames(PCharlotte_color_00_15) <- c("Year","Color","SO4","NO3")

Jordal_test <- data.frame(Jordal_color_00_15$SO4, Jordal_color_00_15$Color)
colnames(Jordal_test) <- c("SO4", "Color")

#fit a linear regression model with year as control variable
Jordal_color_SO4_NO3_year <- lm(Color~SO4+SO4*Year+NO3+NO3*Year,data = Jordal_color_00_15, scale = TRUE, center = TRUE)
summary(Jordal_color_SO4_NO3_year)

Jordal_color_SO4_NO3 <- lm(Color~SO4+NO3,data = Jordal_color_00_15, scale = TRUE, center = TRUE)
summary(Jordal_color_SO4_NO3)

calc.relimp(Jordal_color_SO4_NO3, type = c("lmg"), rela = TRUE)

#--------------PCA---------------
#gather the data for Jordal in one matrix
#define annual temperature and rainfall
PCharlotte_annual_climate <- function(table, start_year, stop_year){
    rainfall_mean <- c()
    T_max_mean <- c()
    year_list <- table$Year
    for (year in start_year:stop_year){
        rainfall_mean <- append(rainfall_mean, sum(table$T_max[year_list == year], na.rm = T))
        T_max_mean <- append(T_max_mean, mean(table$T_max[year_list == year], na.rm = T))
    }
    new_water_table <- data.frame(start_year:stop_year, rainfall_mean, T_max_mean)
    colnames(new_water_table) <- c("Year", "Rainfall", "T_max")
    return(new_water_table)
}

#to exclude T_min we find the correlation between T_max and T_min
#remove NA values
PCharlotte_temp_noNA <- data.frame(PCharlotte_rainfall_months$T_max, PCharlotte_rainfall_months$T_min)
PCharlotte_temp_noNA <- na.omit(PCharlotte_temp_noNA)
cor(PCharlotte_temp_noNA$PCharlotte_rainfall_months.T_max, PCharlotte_temp_noNA$PCharlotte_rainfall_months.T_min)

PCharlotte_annual_color <- annual_color(PCharlotte_water_data, 2000,2015)
PCharlotte_climate_matrix <- PCharlotte_annual_climate(PCharlotte_rainfall_months, 2000,2015)

PCharlotte_matrix <- data.frame(PCharlotte_annual_color$`Mean color`, PCharlotte_climate_matrix,
                PCharlotte_yearly$NDVI[1:16], PCharlotte_acid$SO4)
colnames(PCharlotte_matrix) <- c("Colour","Year", "Rainfall", "Temp", "NDVI", "SO4")
rownames <- seq(2000,2015,1)
rownames(PCharlotte_matrix) <- as.character(rownames)
write_xlsx(PCharlotte_matrix, "PCharlotte_PCA_matrix.xlsx")

PCharlotte_PCA <- prcomp(PCharlotte_matrix[,-2], scale=TRUE)
PCharlotte_PCA$rotation
autoplot(PCharlotte_PCA, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
     main = "Port Charlotte", label = T, label.size = 3, shape = F, scale = 0)
summary(PCharlotte_PCA)

PCharlotte_PCA_noyear <- prcomp(PCharlotte_matrix[,-2], scale=TRUE)
PCharlotte_PCA_noyear$rotation[,2]
autoplot(PCharlotte_PCA_noyear, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
     main = "Port Charlotte", label = T, label.size = 3, shape = F, scale = 0)

biplot(PCharlotte_PCA, xlabs = seq(2000,2015,1), cex = c(0.5,0.8), col = c("black","red"),
    xlim = c(-3,2), ylim = c(-3,2), scale = 0)
```

Bracadale.R

```
#Analyzing data from Bracadale ----------------

library("readxl")
library("timetools")
#read in the data
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Bracadale Farge.xlsx")

#handling the data for date and color. Make a model for color vs date
Bracadale_water_data <- na.omit(water_data) #get rid of the NA values
colnames(Bracadale_water_data) <- c("Date","Color")
Bracadale_water_data$Color <- as.numeric(Bracadale_water_data$Color) #make color data numeric
Bracadale_water_data <- Bracadale_water_data[order(Bracadale_water_data$Date),]

#fit a Theil-Sen estimator
Bracadale_water_data$Num_date <- as.numeric(Bracadale_water_data$Date) #add column with Num_date
Bracadale_color_poly1_TS <- mblm(Color~Num_date, dataframe = Bracadale_water_data, repeated = FALSE)
summary(Bracadale_color_poly1_TS)
Bracadale_color_predictions_TS <- predict.lm(object = Bracadale_color_poly1_TS)
plot(Bracadale_water_data$Date, Bracadale_water_data$Color, xlab = "date", ylab = "colour (mg Pt/L)",
    cex = 0.75, pch = 20, main = "Bracadale")
lines(Bracadale_water_data$Date, Bracadale_color_predictions_TS, lwd = 3, col = "red")

#fit polynomial models of degree 1 on color vs days after January 1 2000
Bracadale_color_poly1 <- lm(Color~Date, data = Bracadale_water_data)
summary(Bracadale_color_poly1)

Bracadale_color_predictions <- predict.lm(object = Bracadale_color_poly1)
#make scatter plot and plot of model
plot(Bracadale_water_data$Date, Bracadale_water_data$Color, xlab = "date", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Bracadale")
lines(Bracadale_water_data$Date, Bracadale_color_predictions, lwd = 3, col = "red")



#find slope of linear fitted line
days <- 5598
slope <- (predictions[length(predictions)]-predictions[1])/days

#function for computing the mean color in each year
annual_color <- function(table, start_year, stop_year){
  color_mean <- c()
  year_list <- table$Date
  year_list <- POSIXst(year_list, "year")
  year_list <- year_list@subtime
  for (year in start_year:stop_year){
    color_mean <- append(color_mean, mean(table$Color[year_list == year]))
  }
  new_water_table <- data.frame(start_year:stop_year, color_mean)
  colnames(new_water_table) <- c("Year", "Mean color")
  return(new_water_table)
}

#create a table with mean color for each year
water_table01_16 <- annual_color(water_data, 2001, 2016)
plot(water_table01_16$Year, water_table01_16$`Mean color`, xlab = "Year", ylab = "Color (mg Pt/l)", cex = 0.75, pch = 20)

#handle rainfall
path <- setwd("M:/Master thesis/Waterwork data")
climate_data <- read_excel("Scotland_climate.xlsx")
#set up a matrix with Bracadale climate data
Bracadale_climate <- data.frame(climate_data$Tiree, climate_data$...13, climate_data$...14)
Bracadale_climate <- Bracadale_climate[2:nrow(Bracadale_climate),]
colnames(Bracadale_climate) <- c("max temp", "min temp", "rainfall")

#define years list in order to plot season rainfall data for each year later
years <- c("2000-01-01","2001-01-01","2002-01-01","2003-01-01",
           "2004-01-01","2005-01-01","2006-01-01","2007-01-01","2008-01-01",
           "2009-01-01","2010-01-01","2011-01-01","2012-01-01","2013-01-01",
           "2014-01-01","2015-01-01","2016-01-01","2017-01-01")
years = as.POSIXct(years)

seconds_in_year <- 3600*24*365.25

#write temperatures and dates as numeric
Bracadale_climate$`max temp` <- as.numeric(Bracadale_climate$`max temp`)
Bracadale_climate$`min temp` <- as.numeric(Bracadale_climate$`min temp`)
Bracadale_climate$rainfall <- as.numeric(Bracadale_climate$rainfall)

#want to rewrite the dates to POSIXct format
x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=201), "%Y-%m-%d")
Bracadale_climate$Date <- as.POSIXct(months) #convert dates to POSIXct format

#look at rainfall, plot rainfall against date
plot(Bracadale_climate$Date, Bracadale_climate$rainfall, cex = 0.75, pch = 20,
    type = "h", xlab = "date", ylab = "rainfall", main = "Bracadale")

#create a dataframe with rainfall and temperature of Bracadale per year
Bracadale_year <- data.frame(years[1:16], Bracadale_rainfall_00_15,
                             Bracadale_maxtemp_00_15, Bracadale_mintemp_00_15)
colnames(Bracadale_year) <- c("Year","Rainfall (mm)","Max temp (°C)", "Min temp (°C)")
Bracadale_year$Num_year <- as.numeric(Bracadale_year$Year)
Bracadale_year$`Max temp (°C)` <- as.numeric(Bracadale_year$`Max temp (°C)`)
Bracadale_year$`Min temp (°C)` <- as.numeric(Bracadale_year$`Min temp (°C)`)

#plot the rainfall for each year for Bracadale
plot(years[1:16], Bracadale_rainfall_00_15, ylim = c(50,1600), xlab = "year",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Bracadale")
#fit a linear model of rainfall as a function of year
```

```
Bracadale_year_rainfall_poly1 <- lm(`Rainfall (mm)`~Year, data = Bracadale_year)
summary(Bracadale_year_rainfall_poly1)

#fit a Theil-Sen estimator of rainfall as a function of year
Bracadale_year_rainfall_poly1_TS <- mblm(`Rainfall (mm)`~Num_year, data = Bracadale_year)
summary(Bracadale_year_rainfall_poly1_TS)
#compute yearly increase
coef(Bracadale_year_rainfall_poly1_TS)[2]*seconds_in_year
Bracadale_year_rainfall_TS_predictions <- predict.lm(object = Bracadale_year_rainfall_poly1_TS)
plot(Bracadale_year$Year, Bracadale_year$`Rainfall (mm)`, xlab = "year",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Bracadale", ylim = c(50,1600))
lines(Bracadale_year$Year, Bracadale_year_rainfall_TS_predictions, col = "red", lwd = 3)

#plot temperature against year
plot(Bracadale_year$Year, Bracadale_year$`Max temp (°C)`, ylim = c(3,15), col = "red", xlab = "year",
    ylab = "max/min temperature (°C)", type = "l", lwd = 3, main = "Bracadale")
par(new = T)
#plot the min temperature in the summer months
plot(years[1:16], Bracadale_year$`Min temp (°C)`, ylim = c(3,15), col = "blue", xlab = "year",
    ylab = "max/min temperature (°C)", type = "l", lwd = 3, main = "Bracadale")
legend(years[1],5.75, c("max temp","min temp"), col=c("red","blue"), cex = 0.55, lty = 1:1, lwd = 2)

#fit a model for max and min temperature as a function of year
Bracadale_year_maxtemperature_poly1 <- lm(`Max temp (°C)`~Year, data = Bracadale_year)
summary(Bracadale_year_maxtemperature_poly1)
Bracadale_year_mintemperature_poly1 <- lm(`Min temp (°C)`~Year, data = Bracadale_year)
summary(Bracadale_year_mintemperature_poly1)

#fit a Theil-Sen estimator for max and min temperature as a function of year
Bracadale_year_maxtemperature_poly1_TS <- mblm(`Max temp (°C)`~Num_year, data = Bracadale_year)
summary(Bracadale_year_maxtemperature_poly1_TS)

Bracadale_year_mintemperature_poly1_TS <- mblm(`Min temp (°C)`~Num_year, data = Bracadale_year)
summary(Bracadale_year_mintemperature_poly1_TS)

#compute yearly increase
coef(Bracadale_year_rainfall_poly1_TS)[2]*days_in_year
Bracadale_year_rainfall_TS_predictions <- predict.lm(object = Bracadale_year_rainfall_poly1_TS)
plot(Bracadale_year$Year, Bracadale_year$`Rainfall (mm)`, xlab = "year",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Bracadale", ylim = c(50,1600))
lines(Bracadale_year$Year, Bracadale_year_rainfall_TS_predictions, col = "red", lwd = 3)

#fit a model for rainfall as a function of date
Bracadale_year <- data.frame(years[1:16], Bracadale_rainfall_00_15)
colnames(Bracadale_year) <- c("Year","Rainfall (mm)")
Bracadale_rainfall_poly1 <- lm(years[1:16]~(Bracadale_rainfall_00_15))
summary(temp_year_poly1)

#fit a Theil-sen estimator for temperature against year
temp_year_poly1_TS <- mblm(`Middeltemperatur (år)`~Num_year, dataframe = temp_data_year, repeated = FALSE)
summary(temp_year_poly1_TS)

#plot summer months over the years
June_indexes <- seq(6,198,12)
July_indexes <- seq(7,199,12)
August_indexes <- seq(8,200,12)
#merge the lists
summer_indexes <- c(June_indexes, July_indexes, August_indexes)
summer_indexes <- sort(summer_indexes)
#plot the rainfall in the summer months
plot(Bracadale_climate$Date[summer_indexes], Bracadale_climate$rainfall[summer_indexes], xlab = "Summer months",
    ylab = "Rainfall", type = "h")

#plot the temperature in the summer months
plot(years[1:17], Bracadale_rainfall_summer_00_16, xlab = "summer",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Bracadale")


#plot the temperature in the spring months
plot(years[1:16], Bracadale_rainfall_fall_00_15, xlab = "fall",
    ylab = "rainfall (mm)", type = "h", lwd = 3, main = "Bracadale")

#-----------------look at temperature---------------
#plot max and min temperature as a function of date
plot(Bracadale_climate$Date, Bracadale_climate$`max temp`, cex = 0.75, pch = 20, ylim = c(0,20),
    type = "l", xlab = "date", ylab = "temperature", main = "Bracadale", col = "red")
par(new = T)
plot(Bracadale_climate$Date, Bracadale_climate$`min temp`, cex = 0.75, pch = 20, ylim = c(0,20),
    type = "l", xlab = "date", ylab = "temperature", main = "Bracadale", col = "green")


#plot the max temperature in the summer months
plot(years[1:17], Bracadale_max_temp_summer_00_16, ylim = c(7,18), col = "red", xlab = "summer",
    ylab = "mean of max/min temperature (°C)", type = "l", lwd = 3, main = "Bracadale")
par(new = T)
#plot the min temperature in the summer months
plot(years[1:17], Bracadale_min_temp_summer_00_16, ylim = c(7,18), col = "blue", xlab = "summer",
    ylab = "mean of max/min temperature (°C)", type = "l", lwd = 3, main = "Bracadale")
legend(years[1],9.25, c("max temp","min temp"), col=c("red","blue"), cex = 0.55, lty = 1:1, lwd = 2)


#plot the max temperature in the spring months
plot(years[1:17], Bracadale_max_temp_spring_00_16, ylim = c(0,15), col = "red", xlab = "spring",
    ylab = "mean of max/min temperature (°C)", type = "l", lwd = 3, main = "Bracadale")
par(new = T)
#plot the min temperature in the spring months
plot(years[1:17], Bracadale_min_temp_spring_00_16, ylim = c(0,15), col = "blue", xlab = "spring",
    ylab = "mean of max/min temperature (°C)", type = "l", lwd = 3, main = "Bracadale")
legend(years[1],3.25, c("max temp","min temp"), col=c("red","blue"), cex = 0.55, lty = 1:1, lwd = 2)
```

```
#plot the max temperature in the fall months
plot(years[1:17], Bracadale_max_temp_fall_00_16, ylim = c(5,16), col = "red", xlab = "fall",
     ylab = "mean of max/min temperature (°C)", type = "l", lwd = 3, main = "Bracadale")
par(new = T)
#plot the min temperature in the fall months
plot(years[1:17], Bracadale_min_temp_fall_00_16, ylim = c(5,16), col = "blue", xlab = "fall",
     ylab = "mean of max/min temperature (°C)", type = "l", lwd = 3, main = "Bracadale")
legend(years[1],7, c("max temp","min temp"), col=c("red","blue"), cex = 0.55, lty = 1:1, lwd = 2)

#-----------------fit Seasonal Kendall for Port Charlotte----------

setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Bracadale Farge.xlsx")

#handling the data for date and color. Make a model for color vs date
Bracadale_water_data <- na.omit(water_data) #get rid of the NA values
colnames(Bracadale_water_data) <- c("Date","Color")
Bracadale_water_data$Color <- as.numeric(Bracadale_water_data$Color) #make color data numeric
Bracadale_water_data <- Bracadale_water_data[order(Bracadale_water_data$Date),]
colnames(Bracadale_water_data) <- c("Date","Color")

#see if data is normally distributed
hist(Bracadale_water_data$Color)
Bracadale_water_data$Log_color <- log(Bracadale_water_data$Color)
hist(Bracadale_water_data$Log_color, breaks = seq(1,6,0.1))

#now we want to create a new column with year as a numeric variable
#create function for identifying the year in the date list
find_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,1,4) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

find_month <- function(date_list){
  month_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    month_col <- append(month_col, date_string)
  }
  month_col <- as.numeric(month_col)
  return(month_col)
}

find_season <- function(date_list){
  season_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
      date_string <- 2
    }
    else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
      date_string <- 3
    }
    else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
      date_string <- 4
    }
    else {
      date_string <- 1
    }
    season_col <- append(season_col, date_string)
  }
  return(season_col)
}

Bracadale_year_col <- find_year(Bracadale_water_data$Date)
Bracadale_water_data$Year <- Bracadale_year_col

Bracadale_month_col <- find_month(Bracadale_water_data$Date)
Bracadale_water_data$Month <- Bracadale_month_col

Bracadale_season_col <- find_season(Bracadale_water_data$Date)
Bracadale_water_data$Season <- Bracadale_season_col

#handle December
Bracadale_water_data <- change_december(Bracadale_water_data)

#perform another seasonal Kendall test with 4 seasons with color
Bracadale_SK_rkt_1 <- rkt(date = Bracadale_water_data$Year, y = Bracadale_water_data$Color, block = Bracadale_water_data$Season, rep = "a")
#look at the model values
Bracadale_SK_rkt_1
Bracadale_SK_rkt_1$tau
Bracadale_SK_rkt_1$sl

#perform another seasonal Kendall test with 4 seasons
Bracadale_SK_rkt_2 <- rkt(date = Bracadale_water_data$Year, y = Bracadale_water_data$Color, block = Bracadale_water_data$Month, rep = "a")
#look at the model values
Bracadale_SK_rkt_2
Bracadale_SK_rkt_2$tau
Bracadale_SK_rkt_2$sl

#fit a T-test adjusted for seasonality (TAS), linear regression with year and season as factors
Bracadale_TAS_1 <- lm(Color~ (Year) + as.factor(Season), data = Bracadale_water_data)
summary(Bracadale_TAS_1)
```

```
#fit a linear model
Bracadale_color_poly1 <- lm(Color~Year, data = Bracadale_water_data)
summary(Bracadale_color_poly1)

#fit a TS model
Bracadale_color_TS <- mblm(Color~Year, dataframe = Bracadale_water_data)
summary(Bracadale_color_TS)

plot(Bracadale_water_data$Date, Bracadale_water_data$Color, xlab = "date", ylab = "colour (mg Pt/L)",
     cex = 0.75, pch = 20, main = "Bracadale")
#now make predictions manually
intercept_list <- Bracadale_water_data$Color-Bracadale_SK_rkt_1$B*(Bracadale_water_data$Year-2001)
intercept <- median(intercept_list)
Bracadale_SK_predictions <- intercept + Bracadale_SK_rkt_1$B*seq(0,15,1)
lines(years[2:17], Bracadale_SK_predictions, col = "red", lwd = 3)

#--------------rainfall------------
path <- setwd("M:/Master thesis/Waterwork data")
climate_data <- read_excel("Tiree_climate.xlsx", col_names = FALSE)
Bracadale_rainfall_months <- data.frame(climate_data$...1, climate_data$...2, climate_data$...3,
                                        climate_data$...4, climate_data$...6)
Bracadale_rainfall_months <- na.omit(Bracadale_rainfall_months)
Bracadale_rainfall_months <- Bracadale_rainfall_months[13:204,]
colnames(Bracadale_rainfall_months) <- c("Year","Month","T_max","T_min","Rainfall")
Bracadale_rainfall_months$T_max <- as.numeric(Bracadale_rainfall_months$T_max)
Bracadale_rainfall_months$T_min <- as.numeric(Bracadale_rainfall_months$T_min)
Bracadale_rainfall_months$Rainfall <- as.numeric(Bracadale_rainfall_months$Rainfall)

#find season in Bracadale rainfall
find_rainfall_season <- function(date_list) {
  season_col <- c()
  for (i in 1:length(date_list)) {
    if (date_list[i] > 2 && date_list[i] < 6 ){
      season <- 2
    }
    else if (date_list[i] > 5 && date_list[i] < 9 ){
      season <- 3
    }
    else if (date_list[i] > 8 && date_list[i] < 12 ){
      season <- 4
    }
    else {
      season <- 1
    }
    season_col <- append(season_col, season)
  }
  return(season_col)
}
find_rainfall_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,4,7) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

Bracadale_rainfall_months$Season <- find_rainfall_season(Bracadale_rainfall_months$Month)

#make a function for making a rainfall column in the color matrix
Bracadale_rainfall_correlation <- function(color_table, rainfall_table){
  color_table$Rainfall <- seq(1,nrow(color_table),1)
  for (i in (1:nrow(color_table))){
    year <- color_table$Year[i]
    month <- color_table$Month[i]
    color_table$Rainfall[i] <- rainfall_table$Rainfall[(rainfall_table$Year == year) & (rainfall_table$Month == month)]
  }
  return(color_table)
}

Bracadale_color_rainfall <- Bracadale_rainfall_correlation(Bracadale_water_data, Bracadale_rainfall_months)
#remove NA values
Bracadale_color_rainfall <- na.omit(Bracadale_color_rainfall)
#compute correlation between color and rainfall
cor(Bracadale_color_rainfall$Color, Bracadale_color_rainfall$Rainfall, use = "complete.obs")
#fit linear model
Bracadale_color_rainfall_poly1 <- lm(Color~Rainfall,data = Bracadale_color_rainfall)
summary(Bracadale_color_rainfall_poly1)
plot(Bracadale_color_rainfall$Rainfall, Bracadale_color_rainfall$Color,  xlab = "monthly rainfall (mm)", ylab = "colour (mg Pt/l)",
     cex = 0.75, pch = 20, main = "Bracadale")
lines(Bracadale_color_rainfall$Rainfall,Bracadale_color_rainfall_poly1$fitted.values)

#correlation between color and temperature
Bracadale_temperature_correlation <- function(color_table, temperature_table){
  color_table$Temperature <- seq(1,nrow(color_table),1)
  for (i in (1:nrow(color_table))){
    year <- color_table$Year[i]
    month <- color_table$Month[i]
    color_table$Temperature[i] <- temperature_table$T_max[(temperature_table$Year == year) & (temperature_table$Month == month)]
  }
  return(color_table)
}

Bracadale_color_temperature <- Bracadale_temperature_correlation(Bracadale_water_data, Bracadale_rainfall_months)
#get Temperature and Rainfall into the same matrix
Bracadale_color_temperature$Rainfall <- Bracadale_color_rainfall$Rainfall
Bracadale_color_temperature_rainfall <- Bracadale_color_temperature[,-3:(-5)]
write_xlsx(Bracadale_color_temperature_rainfall, "Bracadale_Date_Color_Temperature_Rainfall.xlsx")
```

```
Bracadale_color_temperature <- na.omit(Bracadale_color_temperature)
#compute correlation between color and temperature
cor(Bracadale_color_temperature$Color, Bracadale_color_temperature$Temperature, use = "complete.obs")
#fit linear model
Bracadale_color_temperature_poly1 <- lm(Color~Temperature,data = Bracadale_color_temperature)
summary(Bracadale_color_temperature_poly1)
plot(Bracadale_color_temperature$Temperature, Bracadale_color_temperature$Color, xlab = "mean monthly temperature (°C)", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Bracadale")
lines(Bracadale_color_temperature$Temperature,Bracadale_color_temperature_poly1$fitted.values, col = "red", lwd = 3)


#handle December
Bracadale_rainfall_months <- change_december(Bracadale_rainfall_months)

#fit SK model for rainfall
Bracadale_SK_rkt_rainfall <- rkt(date = Bracadale_rainfall_months$Year, y = Bracadale_rainfall_months$Rainfall, block = Bracadale_rainfall_months$Season, rep = "a")
Bracadale_SK_rkt_rainfall
#month as block
Bracadale_SK_rkt_rainfall_month <- rkt(date = Bracadale_rainfall_months$Year, y = Bracadale_rainfall_months$Rainfall, block = Bracadale_rainfall_months$Month, rep = "a")
Bracadale_SK_rkt_rainfall_month

#plot rainfall against date
x <- as.POSIXct("2001-01-01")
months <- format(seq(x, by="month", length.out=192), "%Y-%m-%d")
Bracadale_rainfall_months$Months <- as.POSIXct(months)
plot(Bracadale_rainfall_months$Months, Bracadale_rainfall_months$Rainfall, xlab = "date (monthly)",
    ylab = "rainfall (mm)", type = "h", main = "Tiree (Bracadale)", col = "blue")
#now make predictions of rainfall manually
intercept_list <- Bracadale_rainfall_months$Rainfall- Bracadale_SK_rkt_rainfall$B*(Bracadale_rainfall_months$Year-2001)
intercept <- median(intercept_list, na.rm = TRUE)
Bracadale_SK_predictions <- intercept + Bracadale_SK_rkt_rainfall$B*seq(0,16,1)
lines(years[2:18], Bracadale_SK_predictions, col = "red", lwd = 3)


#fit a  SK model for Bracadale temp
Bracadale_SK_rkt_temp_max <- rkt(date = Bracadale_rainfall_months$Year, y = Bracadale_rainfall_months$T_max, block = Bracadale_rainfall_months$Season, rep = "a")
Bracadale_SK_rkt_temp_max

Bracadale_SK_rkt_temp_min <- rkt(date = Bracadale_rainfall_months$Year, y = Bracadale_rainfall_months$T_min, block = Bracadale_rainfall_months$Season, rep = "a")
Bracadale_SK_rkt_temp_min
#plot temperature against date with monthly resolution
plot(Bracadale_rainfall_months$Months, Bracadale_rainfall_months$T_max, xlab = "date (monthly)",
    ylab = "max/min temperature (°C)", type = "l", main = "Tiree (Bracadale)", col = "red", lwd = 2, ylim = c(-4,20))
par(new = T)
plot(Bracadale_rainfall_months$Months, Bracadale_rainfall_months$T_min, xlab = "date (monthly)",
    ylab = "max/min temperature (°C)", type = "l", main = "Tiree (Bracadale)", col = "blue", lwd = 2, ylim = c(-4,20))
legend(Bracadale_rainfall_months$Months[1], 0, c("max temp","min temp"), col=c("red","blue"), cex = 0.75, lty = 1:1, lwd = 2)


#fit a TAS model for temperature
Bracadale_TAS_temp <- lm(`Middeltemperatur (døgn)`~ (Year) + as.factor(Season), data = Bracadale_temp_day)
summary(Bracadale_TAS_temp)

#fit TAS and SK model for NDVI
#fit SK model
Bracadale_SK_rkt_NDVI <- rkt(date = Bracadale_yearly_shape$year, y = Bracadale_yearly_shape$NDVI)
Bracadale_SK_rkt_NDVI

#test a Theil-Sen estimator
Bracadale_Mann_Kendall_rkt_NDVI <- mblm(NDVI~year, dataframe = Bracadale_yearly, repeated = F)
summary(Bracadale_Mann_Kendall_rkt_NDVI) #different result than SK model

#fit linear model (because there is no seasonality)
Bracadale_TAS_temp <- lm(Bracadale_yearly$NDVI~Bracadale_yearly$year)
summary(Bracadale_TAS_temp)

#plot NDVI
#now we plot mean NDVI values for each year, as a function of year
plot(Bracadale_yearly$year, Bracadale_yearly$NDVI, type = "l", ylim = c(0.5,0.8),
    ylab = "NDVI", xlab = "year", cex = 0.75, pch = 20, lwd = 3, main = "Bracadale", xaxt = "n")
axis(1, at = seq(2000,2016,1))
Bracadale_NDVI_shape_predictions_TS <- predict.lm(Bracadale_Mann_Kendall_rkt_NDVI)
lines(Bracadale_yearly$year, Bracadale_NDVI_shape_predictions_TS, lwd = 3, col = "red")

#---------------acid deposition---------------
#fit Theil-Sen estimator for SO4
Bracadale_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Bracadale_acid, repeated = FALSE)
summary(Bracadale_sulfate_year_poly1_TS)

Bracadale_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Bracadale_acid, repeated = FALSE)
summary(Bracadale_nitrate_year_poly1_TS)

plot(Bracadale_acid$Year, Bracadale_acid$SO4, type = "l", col = "red", ylim = c(0,500),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Bracadale", xaxt = "n")
par(new = T)
plot(Bracadale_acid$Year, Bracadale_acid$NO3, type = "l", col = "green", ylim = c(0,500),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Bracadale", xaxt = "n")
legend(Bracadale_acid$Year[1], 100, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)
axis(1, at = seq(2001,2016,1))

predictions_sulfate_TS <- predict.lm(Bracadale_sulfate_year_poly1_TS)
lines(Bracadale_acid$Year, predictions_sulfate_TS, lwd = 3, col = "firebrick")
predictions_nitrate_TS <- predict.lm(Bracadale_nitrate_year_poly1_TS)
lines(Bracadale_acid$Year, predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#fit a linear model
Bracadale_sulfate_year_poly1 <- lm(Bracadale_acid$SO4~Bracadale_acid$Year)
summary(Bracadale_sulfate_year_poly1)

Bracadale_nitrate_year_poly1 <- lm(Bracadale_acid$NO3~Bracadale_acid$Year)
```

```
summary(Bracadale_nitrate_year_poly1)

predictions_sulfate <- predict.lm(Bracadale_sulfate_year_poly1)
lines(Bracadale_shape_SO4$Year, predictions_sulfate, lwd = 3, col = "firebrick")
predictions_nitrate <- predict.lm(Bracadale_nitrate_year_poly1)
lines(Bracadale_shape_NO3$Year, predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a mixed linear model of color as a function of SO4 and NO3
#compute correlation between SO4 and NO3
cor(Bracadale_acid$SO4, Bracadale_acid$NO3)

#first we have to collect the color into mean yearly values
Bracadale_color_00_15 <- annual_color(water_data, 2000, 2015)
#add NO3 and SO4 to this model
Bracadale_color_00_15$SO4 <- Bracadale_shape_SO4$SO4
Bracadale_color_00_15$NO3 <- Bracadale_shape_NO3$NO3
colnames(Bracadale_color_00_15) <- c("Year","Color","SO4","NO3")

Jordal_test <- data.frame(Jordal_color_00_15$SO4, Jordal_color_00_15$Color)
colnames(Jordal_test) <- c("SO4", "Color")

#fit a linear regression model with year as control variable
Jordal_color_SO4_NO3_year <- lm(Color~SO4+SO4*Year+NO3+NO3*Year,data = Jordal_color_00_15, scale = TRUE, center = TRUE)
summary(Jordal_color_SO4_NO3_year)

Jordal_color_SO4_NO3 <- lm(Color~SO4+NO3,data = Jordal_color_00_15, scale = TRUE, center = TRUE)
summary(Jordal_color_SO4_NO3)

calc.relimp(Jordal_color_SO4_NO3, type = c("lmg"), rela = TRUE)

#--------------PCA---------------
#get color data
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Bracadale Farge.xlsx")

#handling the data for date and color. Make a model for color vs date
Bracadale_water_data <- na.omit(water_data) #get rid of the NA values
colnames(Bracadale_water_data) <- c("Date","Color")
Bracadale_water_data$Color <- as.numeric(Bracadale_water_data$Color) #make color data numeric
Bracadale_water_data <- Bracadale_water_data[order(Bracadale_water_data$Date),]

#gather the data for Bracadale in one matrix
#define annual temperature and rainfall
Bracadale_annual_climate <- function(table, start_year, stop_year){
  rainfall_mean <- c()
  T_max_mean <- c()
  year_list <- table$Year
  for (year in start_year:stop_year){
    rainfall_mean <- append(rainfall_mean, sum(table$T_max[year_list == year], na.rm = T))
    T_max_mean <- append(T_max_mean, mean(table$T_max[year_list == year], na.rm = T))
  }
  new_water_table <- data.frame(start_year:stop_year, rainfall_mean, T_max_mean)
  colnames(new_water_table) <- c("Year", "Rainfall", "T_max")
  return(new_water_table)
}

#to exclude T_min we find the correlation between T_max and T_min
#remove NA values
Bracadale_temp_noNA <- data.frame(Bracadale_rainfall_months$T_max, Bracadale_rainfall_months$T_min)
Bracadale_temp_noNA <- na.omit(Bracadale_temp_noNA)
cor(Bracadale_temp_noNA$Bracadale_rainfall_months.T_max, Bracadale_temp_noNA$Bracadale_rainfall_months.T_min)

Bracadale_annual_color <- annual_color(Bracadale_water_data, 2001,2016)
Bracadale_climate_matrix <- Bracadale_annual_climate(Bracadale_rainfall_months, 2001,2016)

Bracadale_yearly <- annual_NDVI(Bracadale00_16, 2000, 2016)

Bracadale_matrix <- data.frame(Bracadale_annual_color$`Mean color`, Bracadale_climate_matrix,
                               Bracadale_yearly$NDVI[1:16], Bracadale_acid$SO4)
colnames(Bracadale_matrix) <- c("Colour","Year", "Rainfall", "Temp", "NDVI", "SO4")
rownames <- seq(2001,2016,1)
rownames(Bracadale_matrix) <- as.character(rownames)
write_xlsx(Bracadale_matrix, "Bracadale_PCA_matrix.xlsx")

Bracadale_PCA <- prcomp(Bracadale_matrix[,-2], scale=TRUE)
Bracadale_PCA$rotation
autoplot(Bracadale_PCA, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Bracadale", label = T, label.size = 3, shape = F, scale = 0)
summary(Bracadale_PCA)

Bracadale_PCA_noyear <- prcomp(Bracadale_matrix[,-2], scale=TRUE)
Bracadale_PCA_noyear$rotation[,2]
autoplot(Bracadale_PCA_noyear, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Bracadale", label = T, label.size = 3, shape = F, scale = 0)

Jordal_PCA <- prcomp(Jordal_color_00_15, scale=TRUE)
Jordal_PCA$rotation
autoplot(Jordal_PCA, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Bracadale", label = TRUE, shape = F)
```

Atran.R

```
#Analyzing data from Aatran, Aatrafors ----------------

library("readxl")
library("timetools")
library("mblm")
library(Kendall)
library(EnvStats)
library(rkt)
library(relaimpo)
library(ggplot2)
library(ggfortify)
library(PCAtools)
#read in the data
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "VIVAB Aatran, Aatrafors")

#define years list in order to plot season rainfall data for each year later
years <- c("2000-01-01","2001-01-01","2002-01-01","2003-01-01",
           "2004-01-01","2005-01-01","2006-01-01","2007-01-01","2008-01-01",
           "2009-01-01","2010-01-01","2011-01-01","2012-01-01","2013-01-01",
           "2014-01-01","2015-01-01","2016-01-01")
years = as.POSIXct(years)

seconds_in_year <- 3600*24*365.25

#--------------fit seasonal Kendall--------------
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "VIVAB Aatran, Aatrafors")

Karreberg_water_data <- data.frame(water_data$Date, water_data$Color, water_data$doy) #make a dataframe with only Date and Color
Karreberg_water_data <- na.omit(Karreberg_water_data) #get rid of the NA values
colnames(Karreberg_water_data) <- c("Date","Color","Day")
Karreberg_water_data$Color <- as.numeric(Karreberg_water_data$Color) #make color data numeric
Karreberg_water_data <- Karreberg_water_data[order(Karreberg_water_data$Date),]

#now we want to create a new column with year as a numeric variable
#create function for identifying the year in the date list
find_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,1,4) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

find_month <- function(date_list){
  month_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    month_col <- append(month_col, date_string)
  }
  month_col <- as.numeric(month_col)
  return(month_col)
}

find_season <- function(date_list){
  season_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
      date_string <- 2
    }
    else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
      date_string <- 3
    }
    else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
      date_string <- 4
    }
    else {
      date_string <- 1
    }
    season_col <- append(season_col, date_string)
  }
  return(season_col)
}

Karreberg_water_data$Year <- find_year(Karreberg_water_data$Date)
Karreberg_water_data$Season <- find_season(Karreberg_water_data$Date)

plot(Karreberg_water_data$Season, Karreberg_water_data$Color)
plot(Karreberg_water_data$Day, Karreberg_water_data$Color)
#perform a seasonal Kendall test with 4 seasons
Karreberg_SK_rkt_1 <- rkt(date = Karreberg_water_data$Year, y = Karreberg_water_data$Color, block = Karreberg_water_data$Season, rep = "a")
#look at the model values
Karreberg_SK_rkt_1

Karreberg_TAS_1 <- lm(Color~ (Year) + as.factor(Season), data = Karreberg_water_data)
summary(Karreberg_TAS_1)

#fit for rainfall in Karreberg
Karreberg_rainfall <- read_excel("Karreberg_rainfall.xlsx", col_names = FALSE)
Karreberg_rainfall <- Karreberg_rainfall[1524:nrow(Karreberg_rainfall),] #remove columns before year 2000
Karreberg_rainfall <- data.frame(Karreberg_rainfall$...3, Karreberg_rainfall$...4)
colnames(Karreberg_rainfall) <- c("Date","Rainfall")
```

```
Karreberg_years <- find_year(Karreberg_rainfall$Date)
Karreberg_rainfall$Year <- Karreberg_years

#fit for temperature in Karreberg
Karreberg_temp <- read_excel("Karreberg temperature.xlsx", col_names = FALSE)
Karreberg_temp <- Karreberg_temp[37171:nrow(Karreberg_temp),] #remove columns before year 2000
Karreberg_temp <- data.frame(Karreberg_temp$...1, Karreberg_temp$...3)
colnames(Karreberg_temp) <- c("Date","Temperature")

Karreberg_years <- find_year(Karreberg_temp$Date)
Karreberg_temp$Year <- Karreberg_years

#-----------------fit Seasonal Kendall for Karreberg----------

setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "VIVAB Aatran, Aatrafors")

#handling the data for date and color. Make a model for color vs date
Karreberg_water_data <- data.frame(water_data$Date, water_data$Color, water_data$TOC) #make a dataframe with only Date and Color
Karreberg_water_data <- na.omit(Karreberg_water_data) #get rid of the NA values
colnames(Karreberg_water_data) <- c("Date","Color","TOC")
Karreberg_water_data$Color <- as.numeric(Karreberg_water_data$Color) #make color data numeric
Karreberg_water_data$TOC <- as.numeric(Karreberg_water_data$TOC) #make TOC data numeric
Karreberg_water_data <- Karreberg_water_data[order(Karreberg_water_data$Date),] #sort date in chronological order

#see if data is normally distributed
hist(Karreberg_water_data$Color, breaks = seq(0,300,10))
Karreberg_water_data$Log_color <- log(Karreberg_water_data$Color)
hist(Karreberg_water_data$Log_color, breaks = seq(0,7,0.1))

#now we want to create a new column with year as a numeric variable
#create function for identifying the year in the date list
find_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,1,4) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

find_month <- function(date_list){
  month_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    month_col <- append(month_col, date_string)
  }
  month_col <- as.numeric(month_col)
  return(month_col)
}

find_season <- function(date_list){
  season_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
      date_string <- 2
    }
    else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
      date_string <- 3
    }
    else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
      date_string <- 4
    }
    else {
      date_string <- 1
    }
    season_col <- append(season_col, date_string)
  }
  return(season_col)
}

Karreberg_year_col <- find_year(Karreberg_water_data$Date)
Karreberg_water_data$Year <- Karreberg_year_col

Karreberg_month_col <- find_month(Karreberg_water_data$Date)
Karreberg_water_data$Month <- Karreberg_month_col

Karreberg_season_col <- find_season(Karreberg_water_data$Date)
Karreberg_water_data$Season <- Karreberg_season_col

#function for changing December months to be associated with January/February the year after
change_december <- function(water_table){   #takes in the entire matrix
  index_of_december <- water_table$Month == 12
  print(index_of_december)
  water_table$Year[index_of_december] <- water_table$Year[index_of_december] + 1
  return(water_table)
}
Karreberg_water_data <- change_december(Karreberg_water_data)

#perform another seasonal Kendall test with 4 seasons with color
Karreberg_SK_rkt_1 <- rkt(date = Karreberg_water_data$Year, y = Karreberg_water_data$Color, block = Karreberg_water_data$Season, rep = "a")
#look at the model values
Karreberg_SK_rkt_1
Karreberg_SK_rkt_1$tau
Karreberg_SK_rkt_1$sl
```

```
#perform another seasonal Kendall test with months
Karreberg_SK_rkt_2 <- rkt(date = water_data$Year, y = water_data$Color, block = water_data$Month, rep = "a")
#look at the model values
Karreberg_SK_rkt_2
Karreberg_SK_rkt_2$tau
Karreberg_SK_rkt_2$sl

Karreberg_SK_rkt_TOC <- rkt(date = Karreberg_water_data$Year, y = Karreberg_water_data$TOC, block = Karreberg_water_data$Season, rep = "a")
#look at the model values
Karreberg_SK_rkt_TOC
Karreberg_SK_rkt_1$tau
Karreberg_SK_rkt_1$sl

#manually make predictions for colour
intercept_list <- Karreberg_water_data$Color-Karreberg_SK_rkt_1$B*(Karreberg_water_data$Year-2000)
intercept <- median(intercept_list)
Karreberg_SK_predictions <- intercept + Karreberg_SK_rkt_1$B*seq(0,14,1)
lines(years[1:15], Karreberg_SK_predictions, col = "red", lwd = 3)
plot(Karreberg_water_data$Date, Karreberg_water_data$Color, xlab = "date", ylab = "colour (mg Pt/L)",
     cex = 0.75, pch = 20, main = "Ätran")


#manually make predictions for TOC
intercept_list <- Karreberg_water_data$TOC-Karreberg_SK_rkt_TOC$B*(Karreberg_water_data$Year-2000)
intercept <- median(intercept_list)
Karreberg_SK_predictions_TOC <- intercept + Karreberg_SK_rkt_TOC$B*seq(0,14,1)
lines(years[1:15], Karreberg_SK_predictions_TOC, col = "red", lwd = 3)
plot(Karreberg_water_data$Date, Karreberg_water_data$TOC, xlab = "date", ylab = "TOC (mg/L)",
    cex = 0.75, pch = 20, main = "Ätran")

#fit a T-test adjusted for seasonality (TAS), linear regression with year and season as factors
Karreberg_TAS_1 <- lm(Color~ (Year) + as.factor(Season), data = water_data)
summary(Karreberg_TAS_1)

#--------------rainfall------------
path <- setwd("M:/Master thesis/Waterwork data")
climate_data <- read_excel("Karreberg_rainfall.xlsx", col_names = FALSE)
Karreberg_rainfall_months <- data.frame(climate_data$...3,
                                        climate_data$...4)
Karreberg_rainfall_months <- na.omit(Karreberg_rainfall_months)
Karreberg_rainfall_months <- Karreberg_rainfall_months[1524:6637,]
colnames(Karreberg_rainfall_months) <- c("Date","Rainfall")
Karreberg_rainfall_months$Rainfall <- as.numeric(Karreberg_rainfall_months$Rainfall)

#find season in Karreberg rainfall
find_rainfall_season <- function(date_list){
  season_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
      date_string <- 2
    }
    else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
      date_string <- 3
    }
    else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
      date_string <- 4
    }
    else {
      date_string <- 1
    }
    season_col <- append(season_col, date_string)
  }
  return(season_col)
}
find_rainfall_month <- function(date_list){
  month_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    month_col <- append(month_col, date_string)
  }
  month_col <- as.numeric(month_col)
  return(month_col)
}
find_rainfall_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,1,4) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

Karreberg_rainfall_months$Season <- find_rainfall_season(Karreberg_rainfall_months$Date)
Karreberg_rainfall_months$Month <- find_rainfall_month(Karreberg_rainfall_months$Date)
Karreberg_rainfall_months$Year <- find_rainfall_year(Karreberg_rainfall_months$Date)

#make a function for making a temperature column in the color matrix
Karreberg_rainfall_correlation <- function(color_table, rainfall_table){
  for (i in (1:nrow(color_table))){
    date_index <- color_table$Date[i] == rainfall_table$Date
    date_index <- match(TRUE, date_index)
    color_table$Rainfall[i] <- sum(rainfall_table$Rainfall[(date_index-6):date_index])
  }
  return(color_table)
}
```

```
Karreberg_color_rainfall <- Karreberg_rainfall_correlation(Karreberg_water_data, Karreberg_rainfall_months)

#compute correlation between color and rainfall
cor(Karreberg_color_rainfall$Color, Karreberg_color_rainfall$rainfall)
#fit linear model
Karreberg_color_rainfall_poly1 <- lm(Color~Rainfall,data = Karreberg_color_rainfall)
summary(Karreberg_color_rainfall_poly1)
plot(Karreberg_color_rainfall$Rainfall, Karreberg_color_rainfall$Color, xlab = "weekly rainfall (mm)", ylab = "colour (mg Pt/l)",
     cex = 0.75, pch = 20, main = "Ätran")
lines(Karreberg_color_rainfall$Rainfall,Karreberg_color_rainfall_poly1$fitted.values, col = "red", lwd = 3)

Karreberg_rainfall_months <- change_december(Karreberg_rainfall_months)

Karreberg_rainfall_month_total <- function(matrix){
  list_month_total <- c()
  for (year in 2000:2013){
    for (month in 1:12){
      current_year_matrix <- matrix[matrix$Year == year,]
      month_total <- sum(current_year_matrix$Rainfall[current_year_matrix$Month == month])
      list_month_total <- append(list_month_total, month_total)
    }
  }
  return(list_month_total)
}

#plot rainfall with monthly resolution
Karreberg_rainfall_months_total <- Karreberg_rainfall_month_total(Karreberg_rainfall_months)
x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=168), "%Y-%m-%d")
months <- as.POSIXct(months)
plot(months, Karreberg_rainfall_months_total, xlab = "date (monthly)",
     ylab = "rainfall (mm)", type = "h", main = "Ullared (Ätran)", col = "blue")


#fit SK model for rainfall
Karreberg_SK_rkt_rainfall <- rkt(date = Karreberg_rainfall_months$Year, y = Karreberg_rainfall_months$Rainfall, block = Karreberg_rainfall_months$Season, rep = "a")
Karreberg_SK_rkt_rainfall

#plot rainfall against date (daily resolution)
x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=156), "%Y-%m-%d")
Karreberg_rainfall_months$Months <- as.POSIXct(months)
plot(Karreberg_rainfall_months$Date, Karreberg_rainfall_months$Rainfall, xlab = "date (monthly)",
     ylab = "rainfall (mm)", main = "Kärreberg", col = "blue")

#------------------Temperature------------------
Karreberg_temperature_day <- read_excel("Karreberg temperature.xlsx", col_names = FALSE)
Karreberg_temperature_day <- data.frame(Karreberg_temperature_day$...1,
                                        Karreberg_temperature_day$...3)
Karreberg_temperature_day <- na.omit(Karreberg_temperature_day)
Karreberg_temperature_day <- Karreberg_temperature_day[37171:157298,]
colnames(Karreberg_temperature_day) <- c("Date","Temperature")

Karreberg_temperature_day <- change_december(Karreberg_temperature_day)

#fit a  SK model for NRV temp
Karreberg_SK_rkt_temp <- rkt(date = Karreberg_temperature_day$Year, y = Karreberg_temperature_day$Temperature, block = Karreberg_temperature_day$Season, rep = "a")
Karreberg_SK_rkt_temp

#define a function that computes mean temperature in a month
Karreberg_temperature_month_total <- function(matrix){
  list_month_total <- c()
  for (year in 2000:2013){
    for (month in 1:12){
      current_year_matrix <- matrix[matrix$Year == year,]
      month_total <- mean(current_year_matrix$Temperature[current_year_matrix$Month == month])
      print(month_total)
      list_month_total <- append(list_month_total, month_total)
    }
  }
  return(list_month_total)
}

Karreberg_temperature_day$Year <- find_year(Karreberg_temperature_day$Date)
Karreberg_temperature_day$Month <- find_month(Karreberg_temperature_day$Date)
Karreberg_temperature_day$Season <- find_season(Karreberg_temperature_day$Date)

Karreberg_temperature_months <- Karreberg_temperature_month_total(Karreberg_temperature_day)

#make a function for making a rainfall column in the color matrix
Karreberg_temperature_correlation <- function(color_table, temperature_table){
  color_table$Temperature <- seq(1,nrow(color_table),1)
  for (i in (1:nrow(color_table))){
    date_index <- match(color_table$Date[i], temperature_table$Date) #this is the first date that matches
    color_table$Temperature[i] <- mean(temperature_table$Temperature[(date_index-24*6):(date_index+23)])
  }
  return(color_table)
}

Karreberg_color_temperature <- Karreberg_temperature_correlation(Karreberg_water_data, Karreberg_temperature_day)
#get climate variables into same matrix
Karreberg_color_temperature$Rainfall <- Karreberg_color_rainfall$Rainfall
Karreberg_color_temperature_rainfall <- Karreberg_color_temperature[,-3:(-6)]
write_xlsx(Karreberg_color_temperature_rainfall, "Karreberg_Date_Color_Temperature_Rainfall.xlsx")

#compute correlation between color and rainfall
cor(Karreberg_color_rainfall$Color, Karreberg_cr_rainfall$rainfall)
#fit linear model
Karreberg_color_temperature_poly1 <- lm(Color~Temperature, data = Karreberg_color_temperature)
summary(Karreberg_color_temperature_poly1)
```

```
plot(Karreberg_color_temperature$Temperature, Karreberg_color_rainfall$Color,  xlab = "mean weekly temperature (°C)", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Ätran")
lines(Karreberg_color_rainfall$rainfall,Karreberg_color_rainfall_poly1$fitted.values)

mean(Karreberg_color_rainfall$Rainfall[Karreberg_color_rainfall$Season == 1])
mean(Karreberg_color_rainfall$Rainfall[Karreberg_color_rainfall$Season == 2])
mean(Karreberg_color_rainfall$Rainfall[Karreberg_color_rainfall$Season == 3])
mean(Karreberg_color_rainfall$Rainfall[Karreberg_color_rainfall$Season == 4])

mean(Karreberg_color_temperature$Color[Karreberg_color_temperature$Season == 1])
mean(Karreberg_color_temperature$Color[Karreberg_color_temperature$Season == 2])
mean(Karreberg_color_temperature$Color[Karreberg_color_temperature$Season == 3])
mean(Karreberg_color_temperature$Color[Karreberg_color_temperature$Season == 4])

#plot temperature against date with monthly resolution
plot(months, Karreberg_temperature_months, xlab = "date (monthly)",
    ylab = "mean temperature (°C)", type = "l", main = "Ullared (Ätran)", col = "red", lwd = 2)
par(new = T)
plot(Karreberg_rainfall_months$Months, Karreberg_rainfall_months$T_min, xlab = "date (monthly)",
    ylab = "max/min temperature (°C)", type = "l", main = "Tiree (Port Charlotte)", col = "blue", lwd = 2, ylim = c(-4,20))
legend(Karreberg_rainfall_months$Months[1], 0, c("max temp","min temp"), col=c("red","blue"), cex = 0.75, lty = 1:1, lwd = 2)

#fit a TAS model for temperature
Karreberg_TAS_temp <- lm(`Middeltemperatur (døgn)`~ (Year) + as.factor(Season), data = Karreberg_temp_day)
summary(Karreberg_TAS_temp)

#fit TAS and SK model for NDVI
#fit SK model
Karreberg_SK_rkt_NDVI <- rkt(date = Karreberg_yearly_shape$year, y = Karreberg_yearly_shape$NDVI)
Karreberg_SK_rkt_NDVI

#test a Theil-Sen estimator
Karreberg_Mann_Kendall_rkt_NDVI <- mblm(NDVI~year, dataframe = Åtran_yearly_shape, repeated = F)
summary(Karreberg_Mann_Kendall_rkt_NDVI) #different result than SK model

#fit linear model (because there is no seasonality)
Karreberg_TAS_temp <- lm(Åtran_yearly_shape$NDVI~Åtran_yearly_shape$year)
summary(Karreberg_TAS_temp)

#plot NDVI
#now we plot mean NDVI values for each year, as a function of year
plot(Åtran_yearly_shape$year, Åtran_yearly_shape$NDVI, type = "l", ylim = c(0.5,0.8),
    ylab = "NDVI", xlab = "year", cex = 0.75, pch = 20, lwd = 3, main = "Ätran", xaxt = "n")
axis(1, at = seq(1999,2013,1))
Karreberg_NDVI_shape_predictions_TS <- predict.lm(Karreberg_Mann_Kendall_rkt_NDVI)
lines(Karreberg_yearly_shape$year, Karreberg_NDVI_shape_predictions_TS, lwd = 3)

#---------------acid deposition---------------
#fit Theil-Sen estimator for SO4
Karreberg_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Karreberg_shape_SO4, repeated = FALSE)
summary(Karreberg_sulfate_year_poly1_TS)

Karreberg_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Karreberg_shape_NO3, repeated = FALSE)
summary(Karreberg_nitrate_year_poly1_TS)

plot(Karreberg_shape_SO4$Year, Karreberg_shape_SO4$SO4, type = "l", col = "red", ylim = c(0,1000),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Ätran", xaxt = "n")
par(new = T)
plot(Karreberg_shape_NO3$Year, Karreberg_shape_NO3$NO3, type = "l", col = "green", ylim = c(0,1000),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Ätran", xaxt = "n")
legend(Karreberg_shape_SO4$Year[1], 200, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)
axis(1, at = seq(2000,2013,1))

predictions_sulfate_TS <- predict.lm(Karreberg_sulfate_year_poly1_TS)
lines(Karreberg_shape_SO4$Year, predictions_sulfate_TS, lwd = 3, col = "firebrick")
predictions_nitrate_TS <- predict.lm(Karreberg_nitrate_year_poly1_TS)
lines(Karreberg_shape_NO3$Year, predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#fit a linear model
Karreberg_sulfate_year_poly1 <- lm(Karreberg_shape_SO4$SO4~Karreberg_shape_SO4$Year)
summary(Karreberg_sulfate_year_poly1)

Karreberg_nitrate_year_poly1 <- lm(Karreberg_shape_NO3$NO3~Karreberg_shape_NO3$Year)
summary(Karreberg_nitrate_year_poly1)

predictions_sulfate <- predict.lm(Karreberg_sulfate_year_poly1)
lines(Karreberg_shape_SO4$Year, predictions_sulfate, lwd = 3, col = "firebrick")
predictions_nitrate <- predict.lm(Karreberg_nitrate_year_poly1)
lines(Karreberg_shape_NO3$Year, predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a mixed linear model of color as a function of SO4 and NO3
#compute correlation between SO4 and NO3
cor(Karreberg_shape_SO4$SO4, Karreberg_shape_NO3$NO3)

#first we have to collect the color into mean yearly values
Karreberg_color_00_15 <- annual_color(water_data, 2000, 2015)
#add NO3 and SO4 to this model
Karreberg_color_00_15$SO4 <- Karreberg_shape_SO4$SO4
Karreberg_color_00_15$NO3 <- Karreberg_shape_NO3$NO3
colnames(Karreberg_color_00_15) <- c("Year","Color","SO4","NO3")

#fit a mixed linear model of color as a function of SO4 and NO3
#first we have to collect the color into mean yearly values
Karreberg_color_00_13 <- annual_color(Karreberg_water_data, 2000, 2013)

#add NO3 and SO4 to this model
Karreberg_color_00_13$SO4 <- Karreberg_shape_SO4$SO4
Karreberg_color_00_13$NO3 <- Karreberg_shape_NO3$NO3
colnames(Karreberg_color_00_13) <- c("Year","Color","SO4","NO3")

Karreberg_test <- data.frame(Karreberg_color_00_15$SO4, Karreberg_color_00_15$Color)
```

```
colnames(Karreberg_test) <- c("SO4", "Color")

#fit a linear regression model with year as control variable
Karreberg_color_SO4_NO3_year <- lm(Color~SO4+SO4*Year+NO3+NO3*Year,data = Karreberg_color_00_15, scale = TRUE, center = TRUE)
summary(Karreberg_color_SO4_NO3_year)

#fit a linear regression model with SO4
Karreberg_color_SO4 <- lm(Color~SO4,data = Karreberg_color_00_13)
summary(Karreberg_color_SO4)

Karreberg_SO4_for_plot <- Karreberg_color_00_13$SO4[-13]
#plot colour against sulphate
plot(Karreberg_color_00_13$SO4, Karreberg_color_00_13$Color,
    ylim = c(0,150), xlim = c(150,600), xlab = "SO4 concentration (mg (S/N)/m^2)",
    ylab = "colour (mg Pt/L)", cex = 1.5, pch = 20, main = "Kärreberg")
lines(Karreberg_SO4_for_plot, Karreberg_color_SO4$fitted.values, lwd = 3,
     col = "red")

calc.relimp(Karreberg_color_SO4_NO3, type = c("lmg"), rela = TRUE)

#--------------PCA---------------
#get color data
setwd("M:/Master thesis/Waterwork data")
water_data <- read_excel("Copy of Database NOMiNOR new2.xlsx", sheet = "VIVAB Aatran, Aatrafors")

#handling the data for date and color. Make a model for color vs date
Karreberg_water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
Karreberg_water_data <- na.omit(Karreberg_water_data) #get rid of the NA values
colnames(Karreberg_water_data) <- c("Date","Color")
Karreberg_water_data$Color <- as.numeric(Karreberg_water_data$Color) #make color data numeric
Karreberg_water_data <- Karreberg_water_data[order(Karreberg_water_data$Date),]

#gather the data for Karreberg in one matrix
#calculate annual temperature
Karreberg_temperature_yearly <- c()
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[1:12]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[13:24]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[25:36]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[37:48]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[49:60]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[61:72]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[73:84]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[85:96]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[97:108]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[109:120]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[121:132]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[133:144]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[145:156]))
Karreberg_temperature_yearly <- append(Karreberg_temperature_yearly,mean(Karreberg_temperature_months[157:168]))
#calculate annual rainfall
Karreberg_rainfall_yearly <- c()
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[1:12]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[13:24]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[25:36]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[37:48]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[49:60]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[61:72]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[73:84]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[85:96]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[97:108]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[109:120]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[121:132]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[133:144]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[145:156]))
Karreberg_rainfall_yearly <- append(Karreberg_rainfall_yearly, sum(Karreberg_rainfall_months_total[157:168]))

Karreberg_annual_color <- annual_color(Karreberg_water_data, 2000,2013)

#get NDVI data from former runs
setwd("M:/Master thesis/Waterwork data")
Karreberg_shape_NDVI <- read.csv("Karreberg_yearly_shape.csv")
Karreberg_shape_NDVI <- Karreberg_shape_NDVI[,-1]
Karreberg_shape_NDVI <- Karreberg_shape_NDVI[,-1] #take away first column
Karreberg_yearly_shape <- annual_NDVI(Karreberg_shape_NDVI, 1999,2013)

#compute a colour value for missing 2012 by using the SK model
missing_2012 <- Karreberg_SK_predictions[13] #observation 13 of 15 is 2012 and 15 is 2014 (Jan).

Karreberg_matrix <- data.frame(Karreberg_annual_color, Karreberg_rainfall_yearly, Karreberg_temperature_yearly,
                         Karreberg_yearly_shape$NDVI[1:14], Karreberg_shape_SO4$SO4)

colnames(Karreberg_matrix) <- c("Year", "Colour", "Rainfall", "Temp", "NDVI", "SO4")
Karreberg_matrix$Colour[13] <- missing_2012
rownames <- seq(2000,2013,1)
rownames(Karreberg_matrix) <- as.character(rownames)
write_xlsx(Karreberg_matrix, "Karreberg_PCA_matrix.xlsx")

#Fit a model with colour against sulphate in Åtran
Karreberg_color_SO4_poly1 <- lm(Karreberg_matrix$Colour~Karreberg_matrix$SO4, data = Karreberg_matrix)
summary(Karreberg_color_SO4_poly1)
plot(Karreberg_matrix$SO4, Karreberg_matrix$Colour)
Karreberg_color_SO4 <- function(color_table, SO4_table){
  color_table$SO4 <- seq(1,nrow(color_table),1)
  for (i in 1:nrow(color_table)){
    color_table$SO4[i] <- SO4_table$SO4[color_table$Year[i] == SO4_table$Year]
  }
  return(color_table)
}
Karreberg_year_color_SO4 <- Karreberg_color_SO4(Karreberg_water_data, Karreberg_shape_SO4)
Karreberg_color_sulfate_poly1 <- lm(Color~SO4, data = Karreberg_year_color_SO4)
summary(Karreberg_color_sulfate_poly1)
```

```
plot(Karreberg_year_color_SO4$SO4, Karreberg_year_color_SO4$Color)

Karreberg_PCA <- prcomp(Karreberg_matrix[,-1], scale=TRUE)
Karreberg_PCA$rotation
autoplot(Karreberg_PCA, loadings = TRUE, loadings.label = T, axis.text.x = F,
        main = "Ätran", label = T, label.size = 3, shape = F, scale = 0,
        sizeLoadingsNames = 3)
summary(Karreberg_PCA)

Karreberg_PCA_noyear <- prcomp(Karreberg_matrix[,-1], scale=TRUE)
Karreberg_PCA_noyear$rotation[,2]
autoplot(Karreberg_PCA_noyear, loadings = TRUE, loadings.label = T, axis.text.x = F,
        main = "Ätran", label = T, label.size = 3, shape = F, scale = 0,
        sizeLoadingsNames = 3)

typeof(Karreberg_color_00_13$Color)

sum(Karreberg_rainfall_months_total[1:12])
sum(Karreberg_rainfall_months_total[13:24])
sum(Karreberg_rainfall_months_total[25:36])
sum(Karreberg_rainfall_months_total[37:48])
sum(Karreberg_rainfall_months_total[49:60])
sum(Karreberg_rainfall_months_total[61:72])
sum(Karreberg_rainfall_months_total[73:84])
sum(Karreberg_rainfall_months_total[85:96])
sum(Karreberg_rainfall_months_total[97:108])
sum(Karreberg_rainfall_months_total[109:120])
sum(Karreberg_rainfall_months_total[121:132])
sum(Karreberg_rainfall_months_total[133:144])
sum(Karreberg_rainfall_months_total[145:156])
sum(Karreberg_rainfall_months_total[157:168])
```

Paijanne.R

```
#Analyzing data from HSY Paijanne ----------------

library("readxl")
library("timetools")
library("mblm")
#read in the data
setwd("M:/Master thesis/Waterwork data")
water_data <- read_xlsx("HSY/HSY Päijänne.xlsx", sheet = "1. HSY Päijänne", range = "B1:L62")

#define years list in order to plot season rainfall data for each year later
years <- c("2000-01-01","2001-01-01","2002-01-01","2003-01-01",
           "2004-01-01","2005-01-01","2006-01-01","2007-01-01","2008-01-01",
           "2009-01-01","2010-01-01","2011-01-01","2012-01-01","2013-01-01",
           "2014-01-01","2015-01-01","2016-01-01")
years = as.POSIXct(years)

seconds_in_year <- 3600*24*365.25

#-----------------fit Seasonal Kendall for Port Charlotte----------
setwd("M:/Master thesis/Waterwork data")
water_data <- read_xlsx("HSY/HSY Päijänne.xlsx", sheet = "1. HSY Päijänne", range = "B1:L62")

#handling the data for date and color. Make a model for color vs date
Paijanne_water_data <- data.frame(water_data$Date, water_data$Color) #make a dataframe with only Date and Color
Paijanne_water_data <- na.omit(Paijanne_water_data) #get rid of the NA values
colnames(Paijanne_water_data) <- c("Date","Color")
Paijanne_water_data$Color <- as.numeric(Paijanne_water_data$Color) #make color data numeric
Paijanne_water_data <- Paijanne_water_data[order(Paijanne_water_data$Date),]

Paijanne_TOC <- data.frame(water_data$Date, water_data$TOC) #make a dataframe with only Date and Color
Paijanne_TOC <- na.omit(Paijanne_TOC) #get rid of the NA values
colnames(Paijanne_TOC) <- c("Date","TOC")
Paijanne_TOC$TOC <- as.numeric(Paijanne_TOC$TOC) #make color data numeric
Paijanne_TOC <- Paijanne_TOC[order(Paijanne_TOC$Date),]

#see if data is normally distributed
hist(Paijanne_water_data$Color)
Paijanne_water_data$Log_color <- log(Paijanne_water_data$Color)
hist(Paijanne_water_data$Log_color, breaks = seq(1,6,0.1))

#now we want to create a new column with year as a numeric variable
#create function for identifying the year in the date list
find_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,1,4) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

find_month <- function(date_list){
  month_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    month_col <- append(month_col, date_string)
  }
  month_col <- as.numeric(month_col)
  return(month_col)
}

find_season <- function(date_list){
  season_col <- c()
  for (i in 1:length(date_list)){
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,6,7) #get the 4 first characters, which corresponds to year
    if (as.numeric(date_string) > 2 && as.numeric(date_string) < 6 ){
      date_string <- 2
    }
    else if (as.numeric(date_string) > 5 && as.numeric(date_string) < 9 ){
      date_string <- 3
    }
    else if (as.numeric(date_string) > 8 && as.numeric(date_string) < 12 ){
      date_string <- 4
    }
    else {
      date_string <- 1
    }
    season_col <- append(season_col, date_string)
  }
  return(season_col)
}

Paijanne_year_col <- find_year(Paijanne_water_data$Date)
Paijanne_water_data$Year <- Paijanne_year_col

Paijanne_month_col <- find_month(Paijanne_water_data$Date)
Paijanne_water_data$Month <- Paijanne_month_col

Paijanne_season_col <- find_season(Paijanne_water_data$Date)
Paijanne_water_data$Season <- Paijanne_season_col

Paijanne_color_winter <- mean(Paijanne_water_data$Color[Paijanne_water_data$Season == 1])
Paijanne_color_spring <- mean(Paijanne_water_data$Color[Paijanne_water_data$Season == 2])
Paijanne_color_summer <- mean(Paijanne_water_data$Color[Paijanne_water_data$Season == 3])
Paijanne_color_fall <- mean(Paijanne_water_data$Color[Paijanne_water_data$Season == 4])
```

```
Paijanne_water_data <- change_december(Paijanne_water_data)


#perform another seasonal Kendall test with 4 seasons with color
Paijanne_SK_rkt_1 <- rkt(date = Paijanne_water_data$Year, y = Paijanne_water_data$Color, block = Paijanne_water_data$Season, rep = "a")
#look at the model values
Paijanne_SK_rkt_1
Paijanne_SK_rkt_1$tau
Paijanne_SK_rkt_1$sl

#perform another seasonal Kendall test with 4 seasons
Paijanne_SK_rkt_2 <- rkt(date = Paijanne_water_data$Year, y = Paijanne_water_data$Color, block = Paijanne_water_data$Month, rep = "a")
#look at the model values
Paijanne_SK_rkt_2
Paijanne_SK_rkt_2$tau
Paijanne_SK_rkt_2$sl

Paijanne_TOC$Year <- find_year(Paijanne_TOC$Date)

Paijanne_TOC$Month <- find_month(Paijanne_TOC$Date)

Paijanne_TOC$Season <- find_season(Paijanne_TOC$Date)

Paijanne_TOC<- change_december(Paijanne_TOC)

#perform another seasonal Kendall test with 4 seasons with color
Paijanne_SK_rkt_TOC <- rkt(date = Paijanne_TOC$Year, y = Paijanne_TOC$TOC, block = Paijanne_TOC$Season, rep = "a")
#look at the model values
Paijanne_SK_rkt_TOC
Paijanne_SK_rkt_1$tau
Paijanne_SK_rkt_1$sl

#fit a T-test adjusted for seasonality (TAS), linear regression with year and season as factors
Paijanne_TAS_1 <- lm(Color~ (Year) + as.factor(Season), data = Paijanne_water_data)
summary(Paijanne_TAS_1)

#fit a linear model
Paijanne_color_poly1 <- lm(Color~Year, data = Paijanne_water_data)
summary(Paijanne_color_poly1)

x <- as.POSIXct("2001-01-01")
months <- format(seq(x, by="month", length.out=180), "%Y-%m-%d")

plot(Paijanne_water_data$Date, Paijanne_water_data$Color, xlab = "date", ylab = "colour (mg Pt/L)",
     cex = 0.75, pch = 20, main = "Päijänne")

#manually make predictions for colour
intercept_list <- Paijanne_water_data$Color-Paijanne_SK_rkt_1$B*(Paijanne_water_data$Year-2001)
intercept <- median(intercept_list)
Paijanne_SK_predictions <- intercept + Paijanne_SK_rkt_1$B*seq(0,14,1)
lines(years[2:16], Paijanne_SK_predictions, col = "red", lwd = 3)

intercept_list <- Paijanne_TOC$TOC-Paijanne_SK_rkt_TOC$B*(Paijanne_TOC$Year-2001)
intercept <- median(intercept_list)
Paijanne_SK_predictions_TOC <- intercept + Paijanne_SK_rkt_TOC$B*seq(0,14,1)
plot(Paijanne_TOC$Date, Paijanne_TOC$TOC, xlab = "date", ylab = "TOC (mg/L)",
   cex = 0.75, pch = 20, main = "Päijänne")
lines(years[2:16], Paijanne_SK_predictions_TOC, col = "red", lwd = 3)

#find correlation of TOC and colour
Paijanne_cor_color_TOC <- data.frame(water_data$Date, water_data$Color, water_data$TOC)
Paijanne_cor_color_TOC <- na.omit(Paijanne_water_data) #get rid of the NA values
colnames(Paijanne_water_data) <- c("Date","Color","TOC")

Paijanne_cor_color_TOC$Color <- as.numeric(Paijanne_cor_color_TOC$Color) #make color data numeric
Paijanne_cor_color_TOC$TOC <- as.numeric(Paijanne_cor_color_TOC$TOC) #make color data numeric
cor(Paijanne_cor_color_TOC$Color, Paijanne_cor_color_TOC$TOC)

#--------------rainfall------------
path <- setwd("M:/Master thesis/Waterwork data")
Paijanne_rainfall_data <- read_excel("Paijanne_rainfall.xlsx", sheet = "Observation data", col_names = TRUE)
Paijanne_rainfall_months <- data.frame(Paijanne_rainfall_data$Year, Paijanne_rainfall_data$m, Paijanne_rainfall_data$`Monthly precipitation amount (mm)`)
Paijanne_rainfall_months <- na.omit(Paijanne_rainfall_months)
colnames(Paijanne_rainfall_months) <- c("Year","Month","Rainfall")
Paijanne_rainfall_months$Rainfall <- as.numeric(Paijanne_rainfall_months$Rainfall)

#find season in Paijanne rainfall
find_rainfall_season <- function(date_list) {
  season_col <- c()
  for (i in 1:length(date_list)) {
    if (date_list[i] > 2 && date_list[i] < 6 ){
      season <- 2
    }
    else if (date_list[i] > 5 && date_list[i] < 9 ){
      season <- 3
    }
    else if (date_list[i] > 8 && date_list[i] < 12 ){
      season <- 4
    }
    else {
      season <- 1
    }
    season_col <- append(season_col, season)
  }
  return(season_col)
}
find_rainfall_year <- function(date_list){
  year_col <- c()
  for (i in 1:length(date_list)){
```

```
    date_string <- as.character(date_list[i])
    date_string <- substr(date_string,4,7) #get the 4 first characters, which corresponds to year
    year_col <- append(year_col, date_string)
  }
  year_col <- as.numeric(year_col)
  return(year_col)
}

Paijanne_rainfall_months$Season <- find_rainfall_season(Paijanne_rainfall_months$Month)
#make a function for computing correlation between rainfall and color
Paijanne_rainfall_correlation <- function(color_table, rainfall_table){
  color_table$Rainfall <- seq(1,nrow(color_table),1)
  for (i in (1:nrow(color_table))){
    year <- color_table$Year[i]
    month <- color_table$Month[i]
    color_table$Rainfall[i] <- rainfall_table$Rainfall[(rainfall_table$Year == year) & (rainfall_table$Month == month)]
  }
  return(color_table)
}
Paijanne_color_rainfall <- Paijanne_rainfall_correlation(Paijanne_water_data, Paijanne_rainfall_months)
#compute correlation between color and rainfall
cor(Paijanne_color_rainfall$Color, Paijanne_color_rainfall$Rainfall)
#fit linear model
Paijanne_color_rainfall_poly1 <- lm(Color~Rainfall,data = Paijanne_color_rainfall)
summary(Paijanne_color_rainfall_poly1)
plot(Paijanne_color_rainfall$Rainfall, Paijanne_color_rainfall$Color, xlab = "monthly rainfall (mm)", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Päijänne")
lines(Paijanne_color_rainfall$Rainfall,Paijanne_color_rainfall_poly1$fitted.values)

Paijanne_rainfall_months <- change_december(Paijanne_rainfall_months)

#fit SK model for rainfall
Paijanne_SK_rkt_rainfall <- rkt(date = Paijanne_rainfall_months$Year, y = Paijanne_rainfall_months$Rainfall, block = Paijanne_rainfall_months$Season, rep = "a")
Paijanne_SK_rkt_rainfall

#plot rainfall against date
x <- as.POSIXct("2000-01-01")
months <- format(seq(x, by="month", length.out=192), "%Y-%m-%d")
Paijanne_rainfall_months$Months <- as.POSIXct(months)
plot(Paijanne_rainfall_months$Months, Paijanne_rainfall_months$Rainfall, xlab = "date (monthly)",
    ylab = "rainfall (mm)", type = "h", main = "(Sysmä Joutsjärvi) Päijänne", col = "blue")

#fit a  SK model for Paijanne temp
path <- setwd("M:/Master thesis/Waterwork data")
Paijanne_temperature_data <- read_excel("Paijanne_temperature.xlsx", sheet = "Observation data", col_names = TRUE)
Paijanne_temperature_months <- data.frame(Paijanne_temperature_data$Year, Paijanne_temperature_data$m, Paijanne_temperature_data$`Monthly mean temperature (degC)`)
Paijanne_temperature_months <- na.omit(Paijanne_temperature_months)
colnames(Paijanne_temperature_months) <- c("Year","Month","Temperature")
Paijanne_temperature_months$Temperature <- as.numeric(Paijanne_temperature_months$Temperature)

Paijanne_temperature_months$Season <- find_rainfall_season(Paijanne_temperature_months$Month)

Paijanne_temperature_months <- change_december(Paijanne_temperature_months)

#make a function for computing correlation between temperature and color
Paijanne_temperature_correlation <- function(color_table, temperature_table){
  color_table$Temperature <- rep(NA,nrow(color_table))
  for (i in (1:nrow(color_table))){
    year <- color_table$Year[i]
    month <- color_table$Month[i]
    if (sum((temperature_table$Year == year) & (temperature_table$Month == month)) > 0 ){
      color_table$Temperature[i] <- temperature_table$Temperature[(temperature_table$Year == year) & (temperature_table$Month == month)]
    }
  }
  return(color_table)
}

Paijanne_color_temperature <- Paijanne_temperature_correlation(Paijanne_water_data, Paijanne_temperature_months)
#get Temperature and Rainfall into same matrix
Paijanne_color_temperature$Rainfall <- Paijanne_color_rainfall$Rainfall
Paijanne_color_temperature_rainfall <- Paijanne_color_temperature[,-3:(-5)]
write_xlsx(Paijanne_color_temperature_rainfall, "Paijanne_Date_Color_Temperature_Rainfall.xlsx")

#remove NA values
Paijanne_color_temperature <- na.omit(Paijanne_color_temperature)

#compute correlation between color and temperature
cor(Paijanne_color_temperature$Color, Paijanne_color_temperature$Temperature, use = "complete.obs")
#fit linear model
Paijanne_color_temperature_poly1 <- lm(Color~Temperature,data = Paijanne_color_temperature)
summary(Paijanne_color_temperature_poly1)
plot(Paijanne_color_temperature$Temperature, Paijanne_color_temperature$Color, xlab = "mean monthly temperature (°C)", ylab = "colour (mg Pt/l)",
    cex = 0.75, pch = 20, main = "Päijänne")
lines(Paijanne_color_temperature$temperature,Paijanne_color_temperature_poly1$fitted.values)

#fit SK model for temperature
Paijanne_SK_rkt_temperature <- rkt(date = Paijanne_temperature_months$Year, y = Paijanne_temperature_months$Season, block = Paijanne_temperature_months$Season, rep = "a")
Paijanne_SK_rkt_temperature

#make list of dates to plot temperature against date
temp_2000 <- as.POSIXct("2000-01-01")
temp_2000 <- format(seq(temp_2000, by="month", length.out=11), "%Y-%m-%d")
temp_2001 <- as.POSIXct("2001-01-01")
temp_2001 <- format(seq(temp_2001, by="month", length.out=5), "%Y-%m-%d")
temp_2001_2 <- as.POSIXct("2001-08-01")
temp_2001_2 <- format(seq(temp_2001_2, by="month", length.out=13), "%Y-%m-%d")
temp_2002 <- as.POSIXct("2002-10-01")
temp_2002 <- format(seq(temp_2002, by="month", length.out=2), "%Y-%m-%d")
temp_2003 <- as.POSIXct("2003-01-01")
temp_2003 <- format(seq(temp_2003, by="month", length.out=4), "%Y-%m-%d")
temp_2003_2 <- as.POSIXct("2003-06-01")
```

```
temp_2003_2 <- format(seq(temp_2003_2, by="month", length.out=2), "%Y-%m-%d")
temp_2003_3 <- as.POSIXct("2003-09-01")
temp_2003_3 <- format(seq(temp_2003_3, by="month", length.out=18), "%Y-%m-%d")
temp_2005 <- as.POSIXct("2005-05-01")
temp_2005 <- format(seq(temp_2005, by="month", length.out=1), "%Y-%m-%d")
temp_2005_2 <- as.POSIXct("2005-07-01")
temp_2005_2 <- format(seq(temp_2005_2, by="month", length.out=4), "%Y-%m-%d")
temp_2005_3 <- as.POSIXct("2005-12-01")
temp_2005_3 <- format(seq(temp_2005_3, by="month", length.out=1), "%Y-%m-%d")
temp_2006 <- as.POSIXct("2006-03-01")
temp_2006 <- format(seq(temp_2006, by="month", length.out=13), "%Y-%m-%d")
temp_2007 <- as.POSIXct("2007-05-01")
temp_2007 <- format(seq(temp_2007, by="month", length.out=104), "%Y-%m-%d")

temp_month_list <- c(temp_2000,temp_2001,temp_2001_2,temp_2002,temp_2003,
                     temp_2003_2,temp_2003_3,temp_2005,temp_2005_2,
                     temp_2005_3,temp_2006,temp_2007)
nrow(Paijanne_temperature_months)
Paijanne_temperature_months$Months <- temp_month_list
Paijanne_temperature_months$Months <- as.Date(Paijanne_temperature_months$Months)

#plot temperature against date with monthly resolution
plot(Paijanne_temperature_months$Months, Paijanne_temperature_months$Temperature, xlab = "date (monthly)",
    ylab = "mean temperature (°C)", type = "l", main = "Joutsa Savenaho (Päijänne)", col = "red", lwd = 2)
par(new = T)

#fit a TAS model for temperature
Paijanne_TAS_temp <- lm(`Middeltemperatur (døgn)`~ (Year) + as.factor(Season), data = Paijanne_temp_day)
summary(Paijanne_TAS_temp)

#fit TAS and SK model for NDVI
#fit SK model
Paijanne_SK_rkt_NDVI <- rkt(date = Paijanne_yearly_shape$year, y = Paijanne_yearly_shape$NDVI)
Paijanne_SK_rkt_NDVI

#test a Theil-Sen estimator
Paijanne_Mann_Kendall_rkt_NDVI <- mblm(NDVI~year, dataframe = Paijanne_yearly, repeated = F)
summary(Paijanne_Mann_Kendall_rkt_NDVI) #different result than SK model

#fit linear model (because there is no seasonality)
Paijanne_TAS_temp <- lm(Paijanne_yearly$NDVI~Paijanne_yearly$year)
summary(Paijanne_TAS_temp)

#plot NDVI
#now we plot mean NDVI values for each year, as a function of year
plot(Paijanne_yearly$year, Paijanne_yearly$NDVI, type = "l", ylim = c(0.5,0.8),
    ylab = "NDVI", xlab = "year", cex = 0.75, pch = 20, lwd = 3, main = "Päijänne", xaxt = "n")
axis(1, at = seq(1999,2015,1))
Paijanne_NDVI_shape_predictions_TS <- predict.lm(Paijanne_Mann_Kendall_rkt_NDVI)
lines(Paijanne_yearly$year, Paijanne_NDVI_shape_predictions_TS, lwd = 3, col = "red")

#---------------acid deposition---------------
#fit Theil-Sen estimator for SO4
Paijanne_sulfate_year_poly1_TS <- mblm(SO4~Year, dataframe = Paijanne_acid, repeated = FALSE)
summary(Paijanne_sulfate_year_poly1_TS)

Paijanne_nitrate_year_poly1_TS <- mblm(NO3~Year, dataframe = Paijanne_acid, repeated = FALSE)
summary(Paijanne_nitrate_year_poly1_TS)

plot(Paijanne_acid$Year, Paijanne_acid$SO4, type = "l", col = "red", ylim = c(0,300),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Päijänne", xaxt = "n")
par(new = T)
plot(Paijanne_acid$Year, Paijanne_acid$NO3, type = "l", col = "green", ylim = c(0,300),
    xlab = "year", ylab = "concentration (mg (S/N)/m^2)", lwd = 2.5, main = "Päijänne", xaxt = "n")
legend(Paijanne_acid$Year[1], 50, legend=c("SO4", "NO3"), col=c("red", "green"), lty=1:1, cex=0.75, lwd = 2)
axis(1, at = seq(2001,2015,1))

predictions_sulfate_TS <- predict.lm(Paijanne_sulfate_year_poly1_TS)
lines(Paijanne_acid$Year, predictions_sulfate_TS, lwd = 3, col = "firebrick")
predictions_nitrate_TS <- predict.lm(Paijanne_nitrate_year_poly1_TS)
lines(Paijanne_acid$Year, predictions_nitrate_TS, lwd = 3, col = "forestgreen")

#fit a linear model
Paijanne_sulfate_year_poly1 <- lm(Paijanne_acid$SO4~Paijanne_acid$Year)
summary(Paijanne_sulfate_year_poly1)

Paijanne_nitrate_year_poly1 <- lm(Paijanne_acid$NO3~Paijanne_acid$Year)
summary(Paijanne_nitrate_year_poly1)

predictions_sulfate <- predict.lm(Paijanne_sulfate_year_poly1)
lines(Paijanne_shape_SO4$Year, predictions_sulfate, lwd = 3, col = "firebrick")
predictions_nitrate <- predict.lm(Paijanne_nitrate_year_poly1)
lines(Paijanne_shape_NO3$Year, predictions_nitrate, lwd = 3, col = "forestgreen")

#fit a mixed linear model of color as a function of SO4 and NO3

cor(Paijanne_acid$SO4, Paijanne_acid$NO3)
cor(Paijanne_color_01_15$SO4, Paijanne_color_01_15$NDVI)

#first we have to collect the color into mean yearly values
Paijanne_color_01_15 <- annual_color(Paijanne_water_data, 2001, 2015)
#add NO3 and SO4 to this model
Paijanne_color_01_15$SO4 <- Paijanne_acid$SO4
Paijanne_color_01_15$NO3 <- Paijanne_acid$NO3
#NDVI with time lag, therefore I select NDVI values 2000-2014
Paijanne_color_01_15$NDVI <- Paijanne_yearly$NDVI[1:15]
colnames(Paijanne_color_01_15) <- c("Year","Color","SO4","NO3","NDVI")

Paijanne_color_SO4_NDVI <- lm(Color~SO4+NDVI,data = Paijanne_color_01_15)
summary(Paijanne_color_SO4_NDVI)
```

```
#fit a model of colour against NDVI
Paijanne_color_NDVI <- lm(Color~NDVI,data = Paijanne_color_01_15)
summary(Paijanne_color_NDVI)
Paijanne_color_NDVI$fitted.values

calc.relimp(Jordal_color_SO4_NO3, type = c("lmg"), rela = TRUE)

Jordal_PCA <- prcomp(Jordal_color_00_15, scale=TRUE)
Jordal_PCA$rotation
autoplot(Jordal_PCA, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Paijanne", label = TRUE, shape = F)

#--------------PCA---------------
#we must run the function in the top of this script to get the colour data
#handle that 2012 is missing

Paijanne_annual_rainfall <- function(table, start_year, stop_year){
  rainfall_sum <- c()
  year_list <- table$Year
  for (year in start_year:stop_year){
    rainfall_sum <- append(rainfall_sum, sum(table$Rainfall[year_list == year]))
  }
  new_water_table <- data.frame(start_year:stop_year, rainfall_sum)
  colnames(new_water_table) <- c("Year", "Rainfall")
  return(new_water_table)
}

Paijanne_annual_temperature <- function(table, start_year, stop_year){
  temperature_mean <- c()
  year_list <- table$Year
  for (year in start_year:stop_year) {
    temperature_mean <- append(temperature_mean, mean(table$Temperature[year_list == year]))
  }
  new_water_table <- data.frame(start_year:stop_year, temperature_mean)
  colnames(new_water_table) <- c("Year", "Temperature")
  return(new_water_table)
}

#gather the data for Paijanne in one matrix
#define annual temperature and rainfall
path <- setwd("M:/Master thesis/Waterwork data")
Paijanne_rainfall_data <- read_excel("Paijanne_rainfall.xlsx", sheet = "Observation data", col_names = TRUE)
Paijanne_rainfall_months <- data.frame(Paijanne_rainfall_data$Year, Paijanne_rainfall_data$m, Paijanne_rainfall_data$`Monthly precipitation amount (mm)`)
Paijanne_rainfall_months <- na.omit(Paijanne_rainfall_months)
colnames(Paijanne_rainfall_months) <- c("Year","Month","Rainfall")
Paijanne_rainfall_months$Rainfall <- as.numeric(Paijanne_rainfall_months$Rainfall)
Paijanne_rainfall_yearly <- Paijanne_annual_rainfall(Paijanne_rainfall_months,2000,2015)

Paijanne_temperature_data <- read_excel("Paijanne_temperature.xlsx", sheet = "Observation data", col_names = TRUE)
Paijanne_temperature_months <- data.frame(Paijanne_temperature_data$Year, Paijanne_temperature_data$m, Paijanne_temperature_data$`Monthly mean temperature (degC)`)
Paijanne_temperature_months <- na.omit(Paijanne_temperature_months)
colnames(Paijanne_temperature_months) <- c("Year","Month","Temperature")
Paijanne_temperature_months$Temperature <- as.numeric(Paijanne_temperature_months$Temperature)

#problem with temperature- lack of observations
Paijanne_temp_12_2000 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 12])
Paijanne_temp_6_2001 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 6])
Paijanne_temp_7_2001 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 7])
Paijanne_temp_9_2002 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 9])
Paijanne_temp_12_2002 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 12])
Paijanne_temp_5_2003 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 5])
Paijanne_temp_8_2003 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 8])
Paijanne_temp_3_2005 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 3])
Paijanne_temp_4_2005 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 4])
Paijanne_temp_6_2005 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 6])
Paijanne_temp_11_2005 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 11])
Paijanne_temp_1_2006 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 1])
Paijanne_temp_2_2006 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 2])
Paijanne_temp_4_2007 <- mean(Paijanne_temperature_months$Temperature[Paijanne_temperature_months$Month == 4])

Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2000,12,Paijanne_temp_12_2000))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2001,6,Paijanne_temp_6_2001))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2001,7,Paijanne_temp_7_2001))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2002,9,Paijanne_temp_9_2002))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2002,12,Paijanne_temp_12_2002))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2003,5,Paijanne_temp_5_2003))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2003,8,Paijanne_temp_8_2003))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2005,3,Paijanne_temp_3_2005))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2005,4,Paijanne_temp_4_2005))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2005,6,Paijanne_temp_6_2005))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2005,11,Paijanne_temp_11_2005))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2006,1,Paijanne_temp_1_2006))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2006,2,Paijanne_temp_2_2006))
Paijanne_temperature_months <- rbind(Paijanne_temperature_months, c(2007,4,Paijanne_temp_4_2007))

Paijanne_temperature_months <- Paijanne_temperature_months[order(Paijanne_temperature_months$Year, Paijanne_temperature_months$Month),]

Paijanne_temperature_yearly <- Paijanne_annual_temperature(Paijanne_temperature_months, 2000,2015)

#get a matrix of mean annual color.
#function for computing the mean color in each year
Paijanne_annual_color <- function(table, start_year, stop_year){
  color_mean <- c()
  year_list <- table$Date
  year_list <- POSIXst(year_list, "year")
  year_list <- year_list@subtime
  for (year in start_year:stop_year){
    color_mean <- append(color_mean, mean(table$Color[year_list == year]))
  }
  new_water_table <- data.frame(start_year:stop_year, color_mean)
  colnames(new_water_table) <- c("Year", "Mean color")
```

```
  return(new_water_table)
}
Paijanne_color_yearly <- Paijanne_annual_color(Paijanne_water_data, 2001,2015)

Paijanne_matrix <- data.frame(Paijanne_color_yearly,Paijanne_rainfall_yearly$Rainfall[2:16],
                        Paijanne_temperature_yearly$Temperature[2:16],
                        Paijanne_yearly$NDVI[1:15], Paijanne_acid$SO4)
colnames(Paijanne_matrix) <- c("Year","Colour","Rainfall", "Temp", "NDVI", "SO4")
rownames <- seq(2001,2015,1)
rownames(Paijanne_matrix) <- as.character(rownames)
write_xlsx(Paijanne_matrix, "Paijanne_PCA_matrix.xlsx")

Paijanne_PCA <- prcomp(Paijanne_matrix[,-1], scale=TRUE)
Paijanne_PCA$rotation
autoplot(Paijanne_PCA, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Päijänne", label = TRUE, label.size = 3, shape = F, scale = 0)
summary(Paijanne_PCA)

#PCA without year
Paijanne_PCA_noyear <- prcomp(Paijanne_matrix[,-1], scale=TRUE)
Paijanne_PCA_noyear$rotation
autoplot(Paijanne_PCA_noyear, loadings = TRUE, loadings.label = TRUE, axis.text.x = TRUE,
        main = "Päijänne", label = TRUE, label.size = 3, shape = F, scale = 0)
summary(Paijanne_PCA)

sum(Paijanne_rainfall_months$Rainfall[1:12])
sum(Paijanne_rainfall_months$Rainfall[13:24])
sum(Paijanne_rainfall_months$Rainfall[25:36])
sum(Paijanne_rainfall_months$Rainfall[37:48])
sum(Paijanne_rainfall_months$Rainfall[49:60])
sum(Paijanne_rainfall_months$Rainfall[61:72])
sum(Paijanne_rainfall_months$Rainfall[73:84])
sum(Paijanne_rainfall_months$Rainfall[85:96])
sum(Paijanne_rainfall_months$Rainfall[97:108])
sum(Paijanne_rainfall_months$Rainfall[109:120])
sum(Paijanne_rainfall_months$Rainfall[121:132])
sum(Paijanne_rainfall_months$Rainfall[133:144])
sum(Paijanne_rainfall_months$Rainfall[145:156])
sum(Paijanne_rainfall_months$Rainfall[157:168])
Paijanne_temperature_months

#fit a model with sulphate and NDVI as predictors
Paijanne_color_SO4_NDVI <- lm(Colour~SO4+NDVI,data = Paijanne_matrix, scale = TRUE, center = TRUE)
summary(Paijanne_color_SO4_NDVI)

#fit a model with NDVI as predictor
Paijanne_color_NDVI <- lm(Colour~NDVI,data = Paijanne_matrix, scale = TRUE, center = TRUE)
summary(Paijanne_color_NDVI)

mean(Paijanne_color_rainfall$Color[Paijanne_color_rainfall$Season == 1])
mean(Paijanne_color_rainfall$Color[Paijanne_color_rainfall$Season == 2])
mean(Paijanne_color_rainfall$Color[Paijanne_color_rainfall$Season == 3])
mean(Paijanne_color_rainfall$Color[Paijanne_color_rainfall$Season == 4])
```