Forecasting cooling water problems in the River Rhine

A feasibility study

Master thesis
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Executive Summary

Cooling water problems in the Netherlands
Warm and dry summers are a problem for the energy supply in the Netherlands. Most power plants use surface water to cool their generators. To protect the aquatic life from thermal pollution, standards have been defined. In warm and dry periods, such as August 2003 and July 2006, there is a cooling water scarcity, which in the worst case could mean a local breakdown of the energy supply. Conflicts arise between economical damage and violating standards. Forecast of high water temperatures and to a lesser extent low flows could enable water managers and the energy sector to anticipate to crises situations. This research evaluated two possibilities to forecast cooling water problems in the Rhine basin on two timescales.

Ten day forecasts
The first timescale was ten day forecasts, which might be used by the energy sector to adapt production levels. A feasibility study was executed on the realisation of a model system for ten day forecast with physical model and data handling technology existing at WL|Delft Hydraulics. FEWS technology makes the operational system technically feasible. The existing water temperature models for the Rhine basin would require further research, especially regarding the (low flow) hydrology.

The uncertainties caused by the meteorological input parameters however cause uncertainties in the water temperature model that are close to the natural variability of the system. Still it is likely that water temperature forecast will be implemented in FEWS-NL and that the meteorological uncertainties will be accepted. It is recommended to improve the low flow hydrology and change the water temperature formulation in a way that it requires less meteorological parameters.

Another important conclusion from this part of the research is that the influence of cooling water restrictions in Germany on Lobith water temperatures is limited. Because meteorological conditions are dominant over thermal dumps, no large water temperature reductions on basin scale may be expected by human intervention within a 10 day time scope. In the addressed crises situations, cooling water dumps are a local problem and reduction measures should be designed to protect the local environment.

Seasonal forecasts
Seasonal forecasts would give water managers and energy sector more time and possibilities to anticipate to crises situations than ten day forecasts. Seasonal forecasting of Northern European weather is difficult, compared to for example forecasting of the climate in the tropic regions or Australia. In the past decade research was done on statistical forecast of summer hydrometeorology with large scale winter oceanic and atmospheric patterns as predictors. These statistical models outperform the physical models. In the second part of this research we evaluated the possibilities of forecasting Lobith water temperatures and discharges in July and August with winter atmospheric and oceanic patterns as predictors.

A correlation analysis found that the North Atlantic Oscillation Index, the Arctic Oscillation Index, the sea surface temperature and the 500 hPa geopotential height fields were significantly correlated to summer water temperature and discharge at Lobith. Because these predictors are highly dependent, multiple correlations are not significantly higher than the correlations of each predictor. The sea surface
temperature and geopotential height field contained most information, but the correlation patterns in these fields were instable.

With the significantly correlated predictors linear regression models were derived. The first series of models contained the North Atlantic Oscillation Index and the Arctic Oscillation Index as predictors. The correlations between the forecast and the response over the test period were 0.4 for July water temperatures, 0.5 for August water temperatures, 0.2 for July discharges and 0.5 for August discharges. A second series of models contained principle components of sea surface temperatures and geopotential heights as predictors, but these models did not outperform the first series.

Because of the low level of explained variance, possibilities of the suggested models for operational purposes are limited. Still the models explain more than climatology.

A forecast system

The predictive skill of the discussed techniques is limited, but forecast systems for ten day and seasonal forecast with these techniques can be developed. It is however important to communicate the uncertainties with users in terms of confidence intervals and chances. Translation of these chances into risks and possible measures could be done by industry and water managers.

The seasonal and ten day predictions could be part of an information system starting in January, which provides users with summer water temperature and discharge forecasts. The forecasts with lags from 10 days up to 3 months were not discussed in this research. Further research into these shorter term seasonal forecasts is recommended.

This research evaluated statistical models for seasonal predictions and physical based models for short term predictions. Better skill may be achieved with combinations of these techniques. An example of a combined application could be a water balance model for seasonal forecast of low flow hydrology. A water temperature relationship for short term forecasts, which requires less meteorological data, could be derived with a data driven modelling approach.
Preface

This document is the report of my Master thesis research. This thesis forms the final part of the Master degree in Water Management at the faculty of Civil Engineering at Delft University of Technology. I performed this research together with WL|Delft Hydraulics.

I would like to thank the graduation committee: Nick van de Giesen, Martin Baptist, Joost Icke and Wim Uijttewaal for their supervision. The past nine months have been an interesting learning experience and I have worked in a stimulating environment. I therefore would like to thank WL|Delft Hydraulics and especially Pascal Boderie, Erwin Meijers, Reinaldo Peñailillo, Hanneke van der Klis, Ferdinand Diermanse, Henk van den Boogaard, Klaas Jan van Heeringen and Ron Passchier, for help, comments and ideas.

Martine Rutten,

Delft, 10 September 2006.
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Introduction

Cooling water scarcity in warm and dry summers

For many years the attention in hydrological extremes in the Rhine basin has focused on floods and inundation problems. Low flow hydrology has received little attention. In the medium dry and very warm summer of 2003 and the month July of last summer issues related to low flows became clearly visible. Farmers in parts of the basin were not allowed to irrigate their crops and harvest was or in case of 2006 will be small. The agricultural sector also suffered from salt intrusion problems. The reduced navigation water depths forced shipping companies to reduce loads. Moreover the power production was endangered, which forms the motive of this research.

A large part of the River Rhine water is used for cooling electricity generators of power plants and other industries’ equipment. In low flow situation the total discharge through cooling water installations is estimated to reach up to 50 % of the total Rhine discharge (Intermediair week 30 / 2006). Cooling water usage is a threat to the environment. If river water temperatures reach values over 32 ºC, most fish will die (CIW, 2004). To protect the environment from thermal pollution, the Dutch water authorities defined standards in 1976, which limited the permitted discharge and temperature of dumped water (CIW, 2004). In the summer of 2003 conflicts arose between violating standards and risk of economical damage and the problem received much public attention. Rijkswaterstaat gave out special permissions to exceed the standards in order to warrant the energy supply. After the summer of 2003, new cooling water standards have been defined (CIW, 2004). Rijkswaterstaat claims that with new approach a better judgement can be made for each individual situation and that the environment is as well as or even better protected. On a national scale however the total of allowed thermal dumps has increased and therefore cooling water scarcity in July 2006 seemed less severe than in August 2003.

The summer of 2003 and 2006 were no exception in the River Rhine basin. After the summer of 2003 the return period of a similar situation was estimated to be 33 years (Table 1), but new estimates that the take last summers into account will probably result in shorter return periods. The summer of 1994 involved even more problems for the energy sector than the summer of 2003, but was less discussed in public press. Expected climate change may cause smaller return periods and the electricity demands are still rising. Another, for this problem, negative development is that the reserve capacity, which warrants energy supply in crisis situations, is decreasing since privatisation has started (Brinkhorst, 2003).

Table 1; estimated return periods for high water temperatures (WT) (Ploumen, 2004).

<table>
<thead>
<tr>
<th>Year</th>
<th>Days WT&gt;23°C</th>
<th>Days WT&gt;24°C</th>
<th>Estimated return period (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1976</td>
<td>13</td>
<td>5</td>
<td>16</td>
</tr>
<tr>
<td>1981</td>
<td>3</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td>1994</td>
<td>46</td>
<td>41</td>
<td>50</td>
</tr>
<tr>
<td>2003</td>
<td>63</td>
<td>39</td>
<td>33</td>
</tr>
</tbody>
</table>
The best solution to the cooling water problems is probably to relocate power plants at locations less vulnerable to cooling water problems, for example near the coast. This is however costly and only feasible on the very long term. Increased use of renewable energy sources, such as solar and wind energy, could pay a small contribution to the reduction of cooling water usage. A higher production efficiency may as well reduce cooling water problems. The construction of cooling towers reduces cooling water problems and has been applied along the river Meuse, where cooling water limitations occur on a yearly basis, and upstream along the German Rhine. Systems with cooling towers are however less efficient than systems with surface water cooling, which shows in higher CO$_2$ emissions. All improvements mentioned here are capital intensive and long term investments. It is questionable if the reductions will even outweigh the increase due to an increase in power production.

**Research objective**

On the shorter term early warning for high water temperatures and low flows could give the energy sector and authorities time to anticipate to crises situations. In general a market demand from water managers for water quality and quantity forecast systems is observed. This research investigates possibilities for forecasting cooling water problems. It gives an answer to the following question:

*How can water managers and users of cooling water be provided with forecasts, which would enable them to anticipate earlier or better to problems?*

Research questions involve the demand of the user, the data availability and available model technologies.

**Report structure**

A first question that arises in the design of any forecasting system is the timescales on which a forecast would be useful to the user, in this case the water authorities and energy sector. In a report on social economic aspects of low flows, Kooiman (2004) suggested two timescales on which forecast of cooling water limitations could be useful. The first timescale is short term, up to 10 day forecast, equal to common meteorological forecasts. This time span approximates the length of stay of water in the River Rhine from the Lake Constance to Lobith. Kooiman (2004) suggested that the energy sector could use short term for prediction to adapt production levels. Early warning on the seasonal time scale could give more possibilities. It could for example enable the energy sector to buy energy abroad or the authorities to set up awareness campaigns. Taking into account the Dutch standards, monthly average water temperatures over 23 ºC are a strong indicator for cooling water problems. A seasonal prediction of chances of exceedance of this limit would therefore be interesting, especially if discharge, the second limiting factor to cooling water usage, can also be estimated. In the two parts of this research we adopt the two timescales that were identified as potential interesting forecasting horizons by Kooiman.

Different technologies as statistical, physical or scenario models can be applied on both timescales. As the physically based short-term flood forecast model FEWS-NL was available at WL|Delft Hydraulics, it seemed logical to pursue a similar modelling approach for cooling water problem forecast at this same timescale. *Part A* presents the results of a feasibility study of this approach.

The skill of seasonal meteorological forecasts based on physical models is still low. Statistical or other data driven models perform in most cases better. Researchers
also used statistical models to predict hydrometeorology on seasonal time scale from large scale atmospheric and oceanic patterns. In Part B is discussed how large scale winter atmospheric and oceanic patterns can be used in forecasting summer water temperature and discharge in the River Rhine.

Though we only evaluated short term predictions with physical models on the one hand and seasonal forecasts on the other hand, combinations are possible and may result in better early warning systems. These combinations fell out of the scope of this research but suggestions are given where the other modelling approach could be used to increase understanding of the system or improve model skills.
Part A:

Short term water temperature predictions for the River Rhine

a feasibility study for physical modelling approach using FEWS and SOBEK DELWAQ
Abstract

The feasibility of a water temperature forecast system for the River Rhine for a period of ten days was evaluated. The system is technically feasible with the FEWS model system technology existing at WL Delft Hydraulics. The sensitivity and uncertainty analysis on an existing water temperature model for the River Rhine has however shown that accumulated errors may be larger than the natural variability of the system. The largest sources of uncertainty are low flow hydrology, radiation and wind. The sensitivity of model results at Lobith for changes in thermal discharges is small compared to the sensitivity to meteorology. The skill of the suggested forecast system is therefore considered small. Still it is likely that water temperature forecast will be implemented in FEWS-NL and that the meteorological uncertainties will be accepted. It is recommended to improve the low flow hydrology and change the water temperature formulation in a way that it requires less meteorological parameters.
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List of abbreviations

DELWAQ  Delft Water Quality  
ECMWF  European Centre for Meteorological Weather Forecasts  
FEWS  Flood Early Warning System  
KNMI  Koninklijk Nederlands Meteorologisch Instituut (Dutch Royal Meteorological Institute)  
MBE  Mean Bias Error  
RMSE  Root Mean Squared Error  
RIZA  Rijksinstituut voor Integraal Zoetwaterbeheer en Afvalwaterbehandeling (Dutch Institute for Inland Water Management and Waste Water Treatment)  
DWD  Deutsche Wetterdienst (Germany’s National Meteorological Service).
1 Introduction

In a study regarding socio-economic effects of low flows, Kooiman (2004) concluded that a water temperature forecast system could be used for assessing water quality, but also be used by the energy sector. Short-term forecasts could be applied to adapt production levels of the plants. Energy producers could be warned for cooling water limitations and the duration of the limitation could be predicted. On the demand site could power consumption could be reduced by organising awareness campaigns.

Since droughts have drawn attention in the last decade, national institutes have monitored drought indicators in summer and limited forecasts have been available. Every fortnight in summer, the Dutch Institute for Inland Water Management and Waste Water Treatment (Rijksinstituut voor Integraal Zoetwaterbeheer en Afvalwaterbehandeling, RIZA) issues drought reports for water managers. A drought report describes the status of the water systems regarding drought and gives a qualitative forecast of expected developments in the next two weeks. The Dutch Royal Meteorological Institute (KNMI, Koninklijk Nederlands Meteorologisch Instituut) publishes water temperature forecasts for stagnant water with a depth of 2 meters. The used model was originally designed for ice forecasts. The forecasted values of the KNMI water temperature model are not valid for rivers, because of their flow characteristics.

The demand for operational forecast systems in water resource management is increasing. Water keepers ask for water quantity and water quality predictions similar to weather forecasts. To fulfil this market demand, WL Delft Hydraulics is developing operational forecast systems. An example is the flood early warning system for the Dutch rivers, FEWS-NL (Werner, 2005). With FEWS-NL up to ten day flow forecasts are made for the Dutch rivers and a warning is given, if flow crosses a certain high threshold, over which floods may occur. FEWS is the generic name for shell applications that regulate the dataflow between a hydrological and a hydraulic model and presents the results of these models. Special attention is paid to data assimilation and crossing of critical thresholds.

The FEWS architecture may also be used for water quality forecasts. An example of a project that is being executed this year is the forecast of Algae blooms in the province Zeeland, and soon a project regarding the forecast of general water quality problems in Singapore Bay will start. The Singapore Bay will be closed to create a fresh water reservoir for drinking water supply and recreation, but these functions may be threatened due to water quality problems. The river, which will discharge into this new reservoir, flows through the city and may therefore have high nutrient and pollution loads.

As another possible water quality application, this study investigates the possibilities to forecast Rhine water temperature with a FEWS application. Though not calibrated for low flows, a hydrologic and a hydrodynamic model are available for the River Rhine basin and used in FEWS-NL. The hydrodynamic model could be extended with a water temperature model. Figure 1 shows possible system architecture. With the model technologies available at WL|Delft Hydraulics a Rhine water temperature model seems technically feasible.
The uncertainties in a forecast system are however larger than in a hindcast system. Where hindcast errors can be reduced through a calibration process that uses observed data for flow and temperature, forecast errors are compounded by forecast errors in precipitation, radiation, air temperature and other meteorological parameters, which are used as model input. In forecasting water quality with physical models, we may risk larger errors than in forecasting flow, as the amount of parameters and therefore the possibility of error propagation is considerably larger, see Figure 2. Drought phenomena have longer timescales than floods (Tallaksen, 2005), which implies that changes in drought indicators as water temperature and low flow may be smaller over ten days than changes in high flows.

Figure 2; the influence of uncertainties and the number of parameters on error propagation. Forecasts involve more uncertainties than hindcasts. As water quality predictions use more parameters than flow predictions for the same area, the chances of error propagation may be larger.
The objective of this research is to assess the forecast skill of a water temperature forecast system. Therefore the forecast uncertainties are compared to the natural variability of the system. If the uncertainties in the model components are larger than the natural variability of the system, the skill of forecasts may be considered small. We evaluate the sensitivity of the water temperature model available at WL|Delft Hydraulics and the uncertainties in a forecast situation. Moreover, a sensitivity analysis on thermal dump can give an idea about the efficiency of production limitations for water temperature reduction in case of crises situations such as the summer of 2003.

A sensitivity analysis of the water temperature model developed by WL|Delft Hydraulics applied to the River Meuse has been carried out by Icke (2003). He concluded that discharge, meteorological conditions and water temperatures of the side river Ruhr were the most influencing parameters to water temperatures. The most important meteorological conditions were radiation air temperature wind speed and relative humidity.
2 Material and methods

2.1 Overview
This paragraph gives a short introduction to the materials and methods used in the feasibility study. The components are further elaborated in the remaining of this chapter. To estimate the uncertainties involved in water temperature forecasts we executed an uncertainty and sensitivity analysis on an existing water temperature model for the River Rhine. This water temperature model was developed for RIZA in a Quick Scan Rhine water temperatures. The Quick Scan model uses DELWAQ water temperature models, based on the heat balance of surface water. Because data on solar radiation, which is an important factor in the heat balance, are scarcely available, the use of solar radiation approximation methods was evaluated. An overview of the parameters, symbols and units is given in Appendix A.

2.2 Heat balance
The water temperature of the River Rhine is influenced by human factors, mainly cooling water discharges, climate variables and river characteristics. Evans (1998) divided the energy budget of a river in three components:

\[ q_n = q_{sn} + q_{bn} + q_f \]  

(1)

Where \( q_n \) is the total net heat exchange, \( q_{sn} \) is the net heat exchange at the air-water interface, \( q_{bn} \) is the net heat exchange at the water bed interface and \( q_f \) is the heat flux due to friction. In case of the River Rhine the power \( W \), discharged with cooling water, is a significant source of heat next to the fluxes described above. The temperature change \( \frac{dT}{dt} \) of a water column in a river with width \( B \), depth \( h \), heat capacity \( c_w \) and density \( \rho_w \) then equals:

\[ \frac{dT_w}{dt} = \frac{1}{hc_w \rho_w} \left( q_n + \frac{W}{B} \right) \]  

(2)

The largest of the three heat fluxes is the flux through the air water interface, which is caused by climate conditions. It comprises of the short wave radiation \( q_{gs} \), the long wave radiation \( q_a \), back radiation \( q_b \), latent heat \( q_l \) and convection \( q_c \). In Figure 3 an indication of the magnitude of the fluxes is given.
Figure 3; Overview of the heat exchange mechanisms at the water surface as caused by weather conditions. The fluxes are short wave radiation $q_g$, the long wave radiation $q_a$, back radiation $q_b$, latent heat $q_l$ and convection $q_c$. The range of magnitude for summer conditions is indicated in W/m² and taken from Van Mazijk (2002).

The magnitude of the fluxes can also be expressed in timescales (Table 2). The time scales of the heat exchange processes have an order of magnitude of one day. This is a factor 10 smaller than the length of stay in the river basin.

Table 2; time scales of heat exchange processes with the atmosphere. The timescale is defined as the time required to heat or cool a water column of 6 meters (assumed average Rhine water depth) 1°C for the given heat flux and average water conditions (density 1000 kg/m³ and heat capacity 4195 J/kg/K).

<table>
<thead>
<tr>
<th>Component</th>
<th>Symbol</th>
<th>Heat flux (W/m²)</th>
<th>Timescale (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Minimum</td>
<td>Maximum</td>
</tr>
<tr>
<td>Short wave radiation</td>
<td>$q_g$</td>
<td>160</td>
<td>220</td>
</tr>
<tr>
<td>Long wave radiation</td>
<td>$q_a$</td>
<td>200</td>
<td>400</td>
</tr>
<tr>
<td>Back radiation</td>
<td>$q_b$</td>
<td>400</td>
<td>460</td>
</tr>
<tr>
<td>Latent heat</td>
<td>$q_l$</td>
<td>220</td>
<td>1100</td>
</tr>
<tr>
<td>Convective heat</td>
<td>$q_c$</td>
<td>0</td>
<td>160</td>
</tr>
<tr>
<td>Length of stay in the basin</td>
<td></td>
<td>-10</td>
<td></td>
</tr>
</tbody>
</table>

The short wave radiation or global radiation depends on geographical position, date, cloudiness and the solar constant. Part of the short wave radiation is absorbed by clouds, vapour and CO₂ and emitted as long wave radiation or atmospheric radiation. The intensity of the long wave radiation depends on cloudiness, air pressure and vapour pressure and is higher on a cloudy day than on a day with clear sky. Both short wave and long wave radiation are not completely absorbed by the water body, but partly reflected. Not only atmospheric particles emit long wave radiation but also the water body itself. This large heat loss component is called back radiation. Evaporation pays another large contribution to cooling of the water. The opposite flux, condensation is seldom found for water systems in temperate climates. Latent heat is the generic term for evaporation and condensation and depends on the climate variables wind speed and relative humidity. The smallest heat exchange component at the air-water interface is conduction, which is driven by the temperature difference at this boundary layer.
At the water bottom heat may be exchanged by *conductive processes*. Moreover, cold ground water enters the water body at the interface as an *advective heat flux*. Ground water in the Rhine basin has a rather constant temperature of 10 to 12 ºC, which is significantly lower than the surface water temperature of the river in summer. The river gains heat through *friction* at the bed and banks, as well as internal turbulence. For small water bodies the river bed may adsorb part of the short wave radiation. If the water column is however deep, only a negligible part of the radiation reaches the river bottom.

### 2.3 Calculation of water temperature with DELWAQ

Following an extensive literature study (Boderie, 2003), WL|Delft Hydraulics developed a water temperature model in the water quality model system DELWAQ. The model was applied and calibrated for the Meuse River (Icke, 2003) and Icke (2005 and 2006) used the model in a Quick Scan and a follow-up study for the River Rhine.

DELWAQ water temperature processes were designed for temperature calculations in heavy modified rivers with many cooling water discharges. Therefore DELWAQ distinguishes between a natural water temperature NatTemp, which is caused by natural heat exchange processes, and a surplus water temperature ModTemp, which is caused by thermal dumps. The modelled temperature Temp equals the sum of NatTemp and ModTemp. For the calculation of NatTemp, a heat balance model HEATBAL is used, whereas ModTemp is calculated with a cooling model EXESS.

#### Heat balance in HEATBAL

HEATBAL neglects the friction heat flux and the convective heat flux to the bed. The hydrology of the basin was simplified in the Rhine water temperature studies (Icke 2005 and 2006). Therefore the other main heat flux at the water bed interface, the heat contribution of groundwater, was also neglected in these studies. The heat balance of surface water in HEATBAL is:

\[
q_n = q_{gn} + q_{an} - q_{bu} + q_{ln} + q_{cn}
\]

Part \( \alpha_g \) of the measured global radiation \( q_g \) is reflected.

\[
q_{gn} = \left(1 - \alpha_g \right) q_g
\]

Average daily values found for the reflection factor or albedo are 0.15 in Switzerland (Kinzelbach, 2004) and 0.1 in the Netherlands (Van Mazijk, 2004). The albedo \( \alpha_a \) of atmospheric radiation is 0.03.

\[
q_{an} = \left(1 - \alpha_a \right) q_a
\]

The atmospheric radiation depends on the air temperature. Stefan and Boltzmann (1884) have determined a constant \( \sigma \), which relates air temperature \( T_a \) to atmospheric radiation of a black body.
\[ q_a = \varepsilon \sigma (T_a + 273.15)^4 \]  

(6)

Where \( \varepsilon \) is the dimensionless emissivity or colour factor. Edinger (1965) found a formulation, which relates the colour factor to cloud cover \( CC \) and vapour pressure \( p_a \):

\[ \varepsilon = 0.74(1 + 0.17CC) + 0.0045(1 - 0.4CC)p_a \]  

(7)

The air vapour pressure is calculated from the saturated vapour pressure, \( p_{sa} \) and the relative humidity, \( RH \):

\[ p_a = RH p_{sa} \]  

(8)

Sweers (1976) derived an equation that is commonly used to obtain the saturated vapour pressure of the air with a temperature \( T_a \):

\[ p_{sa} = 6.131 + 0.467T_a + 0.00898T_a^2 + 0.000527T_a^3 \]  

(9)

The long wave back radiation \( q_b \) can also be calculated as described by Stefan and Boltzmann. Water is almost a perfect black body and its colour coefficient is approximately 0.97.

\[ q_b = \varepsilon \sigma (T_w + 273.15)^4 \]  

(10)

The evaporation or condensation \( q_l \) depends on the wind speed and the relative humidity or the difference between actual vapour pressure and maximum vapour pressure. The water temperature is assumed to be constant during evaporation or condensation.

\[ q_L = \rho_w L_e E \]  

(11)

Where \( L_e \) is the heat of evaporation or the energy required to evaporate one kilogram water. This heat of evaporation depends on the water temperature

\[ L_e = 2.5 \times 10^6 - 2300T_w \]  

(12)

Wind speed \( W \) and the difference between the actual vapour pressure \( p_a \) and \( p_{sw} \) influence the rate of evaporation \( E \).

\[ E = f(W_p)(p_{sw} - p_a) \]  

(13)

The wind speed should be measured at height \( h \), which is in most cases 10 meters. Measurements taken at another altitude \( m \) can be corrected with a roughness coefficient \( k \) for the wind profile:
In literature, many variants of the wind function \( f(W_a) \) can be found. DELWAQ uses default coefficients recommended by Sweers (1976).

\[
f(W_a) = \frac{4.4 + 1.82 W_a}{\rho (T_{\text{refwind}}) \times L_E (T_{\text{refwind}})}
\]  

(15)

Where \( T_{\text{refwind}} \) is the temperature at which the wind function was defined. For the Sweers function this is 15 °C. Bowen (1926) related the convective heat \( q_c \) to the latent heat with the Bowen’s ratio, \( R \):

\[
q_c = R q_L
\]  

(16)

The Bowen’s ratio uses the ratio of the difference between air and water temperature and the saturation of the air. This ratio is multiplied by the Bowens constant \( \beta_g \) to obtain the dimensionless Bowens ratio.

\[
R = \beta_g \frac{T_w - T_a}{p_{sa} - p_a}
\]  

(17)

Bowens constant, incorrectly called constant, depends on the specific heat capacity of air \( c_{pa} \), the air pressure \( P \) and heat of evaporation \( L_E \), which is also determined for latent heat.

\[
\beta = \frac{c_{pa} P}{0.62 L_E}
\]  

(18)

**The surplus temperature in EXESS**

A thermal dump causes a rise in temperature above the natural temperature. This rise is called surplus temperature or in DELWAQ terms ModTemp. EXESS simulates how the water looses this temperature surplus with a cooling model. The approach is based on the assumption that the surplus temperature \( T_s \), determines the change rate of temperature. In the excess temperature model by Sweers (1976), which is used in EXESS, the heat exchange flux \( q_{\text{tot}} \) is represented by a bulk exchange formula:

\[
q_{\text{tot}} = -\lambda(T_s)
\]  

(19)

The heat exchange coefficient \( \lambda \) is a function of the surface temperature and the wind speed at 10 meters above surface level. Sweers (1976) derived the following relation by linearization of the exchange fluxes for back radiation, evaporation and convection:

\[
\lambda = 4.48 + 0.049 T_a + F(W_a) \left( 1.12 + 1.018 T_s + 0.00158 T_s^2 \right)
\]  

(20)
Where the wind function $F(W_a)$ with Sweers’ coefficients can be used:

$$F(W_a) = 4.4 + 1.82 W_a$$  \hspace{1cm} (21)

### 2.4 Short wave radiation approximation for forecasts

Short wave radiation is not found in common weather forecast. Measurements are relatively scarce. Therefore several methods for estimating solar radiation based on other meteorological parameters such as sun hours, cloud fraction and air temperature have been developed. These methods calculate the extraterrestrial radiation based on the sun constant and earth’s rotation. Secondly the amount of radiation which reaches the earth surface is determined. This second step is different for each method. The methodology described below is taken from the WOFOST crop growth simulation model (Supit, 2003) that has been developed by Alterra for the European Commission.

**Calculation of extraterrestrial radiation**

The solar radiation outside the earth’s atmosphere is called extraterrestrial radiation, $I_a$. The extraterrestrial radiation can be derived from the solar constant $I$, which equals 1367 W/m$^2$, by correction for two phenomena. First the distance between the earth and sun $R_a$ is not constant and secondly the solar elevation angle $\gamma$ changes with latitude and season.

$$I_a = I \sin(\gamma) \left( \frac{R_{av}}{R_a} \right)^2$$ \hspace{1cm} (22)

To correct for the distance differences between sun and earth, radiation may be multiplied by the squared ratio between mean distance $R_{av}$ and actual distance $R_a$. This ratio can be approximated with the following series (Partridge, 1976):

$$\left( \frac{R_{av}}{R_a} \right)^2 = 1.0001 + 0.034221 \cos(\beta) + 0.001280 \sin(\beta) + 0.000719 \cos(2\beta) + 0.000077 \sin(2\beta)$$ \hspace{1cm} (23)

$$\beta = \frac{2\pi n}{365} \text{ rad}$$

For the northern hemisphere the sun is higher in the sky during summer and lower in the sky as winter approaches. This is partly caused by tilting of the earth’s axis and can be described with declination, $\delta$ (Duffie, 1991):

$$\delta = \frac{23.5\pi}{180} \cos(\omega_0 t - 2.95)$$ \hspace{1cm} (24)

Where $\omega_0$ is the rotation speed of the earth around the sun and $t$ the time of the year. Apart from seasonal variation the height of the sun lowers as an observer moves away from the equator. The influences of latitude $\phi$ and declination $\delta$ are brought together in the following relationship for the solar elevation angle $\gamma$:
\[
\sin(\gamma) = \sin(\delta)\sin\left(\frac{\pi \phi}{180}\right) - \cos(\delta)\cos\left(\frac{\pi \phi}{180}\right)\cos(\omega_t t) \tag{25}
\]

Solar radiation data available report the daily sum of solar radiation and also DELWAQ requires a daily sum. This sum can be approximated with an integral using the radiation at noon and the day length.

\[
I_a = \frac{2L_d I_{noon}}{\pi} \tag{26}
\]

The day length depends on declination $\phi$ and latitude $\delta$.

\[
L_d = 2 \arccos\left(-\tan(\phi)\tan(\delta)\right) \tag{27}
\]

**Reduction for atmospheric circumstances**

Not all extraterrestrial radiation will reach the earth surface; part will be reflected by clouds or other particles in the atmosphere. Several empirical methods have been developed to determine the radiation, which reaches the earth surface $I_s$. Four methods are described below. The methods use empirical coefficients for several weather stations. While using these coefficients attention should be paid, whether the coefficients were derived for the actual extraterrestrial radiation $I_a$ or for the solar constant $I$.

**Ångström-Prescott**

Ångström (1924) suggested and Prescott (1940) elaborated following method to determine solar radiation at the earth surface $I_s$, if data on sun hours, $n$, are available.

\[
I_s = I_a(A_a + B_a (n/L_d)) \tag{28}
\]

Prescott originally (1940) proposed that $A_a$ is 0.22 and $B_a$ is 0.54. Some researchers however consider that the constants depend on the geographical location (Udo, 2002). Values have therefore been documented for several weather stations.

**Hargreaves**

A simple method to estimate daily global radiation, relating the difference between maximum and minimum temperature to global radiation (Hargreaves, 1985) is:

\[
I_s = I_a A_h \sqrt{(T_{\text{max}} - T_{\text{min}})} + B_h \tag{29}
\]

**Supit**

The Supit or extended Hargreaves method used cloud cover, $CC$, and maximum and minimum temperatures to approximate the radiation at the earth’s surface.
\[ I_s = I_a \left( A_s \sqrt{T_{\text{max}} - T_{\text{min}}} \right) + B_s \sqrt{1 - CC} + C_s \]  \hspace{1cm} (30)

Supit and van Kappel (1998) and van Kappel and Supit (1998) have obtained sets of regression constants for the Hargreaves and the Supit formulae for different weather stations.

**Gill**

This method, which is incorporated in the WL|Delft Hydraulics software Delft3D, uses cloud fraction \( F_B \) to determine solar radiation reaching the earth surface and a factor that describes clear sky radiation \( A_g \). Gill (1982) found the following relationship:

\[ I_s = A_g \cdot F_B \cdot I_a \]  \hspace{1cm} (31)

Gill used 0.76 and Ludikhuize (1996) reported 0.68 for the clear sky coefficient. Two cloud functions can be used. The first one is derived by Sweers (1979);

\[ F_B = 1.0 - 0.65 CC^2 \]  \hspace{1cm} (32)

A second function can be found in Gill (1982):

\[ F_B = 1.0 - 0.4 CC - 0.38 CC^2 \]  \hspace{1cm} (33)

### 2.5 Model Quick Scan Rhine water temperature

The sensitivity and uncertainty analysis was carried out on a water temperature model, which was made in a Quick Scan study on Rhine water temperatures (Icke, 2005). As the name Quick Scan implies this model gives a rather rough simplification of the situation. In this paragraph we give a short description of the model instrument and the most important assumptions. For a complete description we refer to Icke (2005).

The Quick Scan model consists of a water quantity and a water quality component. The water quantity is calculated with SOBEK (the hydrodynamic model system developed by WL|Delft Hydraulics) and the water temperature with the DELWAQ water temperature model as described in paragraph 2.3.

The model reaches from Lake Constance till Lobith including only the larger side rivers Aare, Neckar, Main and Moselle starting from Trier. The hydrodynamics in the model is schematized as steady flow with constant discharges over a month. The water temperature was not available for all lateral discharges. Therefore the model used measurements of Rekingen, Koblenz, Lobith or Aare for the nearest unknown laterals. As mentioned before, all lateral discharges have surface water temperatures, so the influence of cooler groundwater input was neglected.
The model contained the permitted thermal dumps and no actual cooling water discharge data. Cumulative values of the large thermal dumps per river branch are depicted in Figure 4. In warm summers stricter limitations may occur to obey standards. In this case the assumption of permitted dumps may lead to an overestimation of the cooling water discharges and water temperatures.

The meteorological data were given for five weather stations in the basin. For each branch the meteorological conditions were determined with a weighted average of these stations. Global radiation data were not available for the weather stations in Germany. Therefore data from the KNMI station de Bilt were used for this parameter over whole basin.

For the remainder of this report we adopt the basin division applied by Icke (2006). He divided the Rhine in three parts. The part from the Bodensee to Mannheim is defined as the higher Rhine, the part from Mannheim to Trier as the middle Rhine and the part from Koblenz to Lobith as the lower Rhine. This convention differs from the official division.

Most simulations in the sensitivity and uncertainty analysis were executed for the summer of 2000. This summer can be considered an average summer regarding hydro meteorological conditions (Icke, 2005). Some calculations were done with data of the 2003 summer, which was an extremely hot and relative dry summer.
2.6 Sensitivity and uncertainty analysis

The sensitivity and uncertainty analysis evaluated the influence of parameter variation on model results. Special attention was paid to uncertainties, which are clearly present in a forecast model, but play a minor role in models used for hindcasting, like the propagation of uncertainties in weather forecasts and the use of approximation methods for solar radiation.

The water temperature depends on discharge, the incoming discharge’s temperature, thermal dump and the weather conditions. The sensitivity of the model is the reaction of the model outcome to any change in the input. Figure 5 gives an example of a possible model reaction to a change in air temperature.

![Figure 5; example of a sensitivity analysis on water temperature by changing the air temperature. Variation of the input parameter air temperature causes a change in the output parameter water temperature.](image)

If the model is used for prediction, the input parameters will incorporate an increasing uncertainty over time. For example, the air temperature predictions issued by the KNMI show an increasing confidence band width as the predicted time increases. Possible errors in air temperature predictions may propagate in the water temperature model. Figure 6 shows another example of uncertainty propagation for a solar radiation approximation method.

![Figure 6; propagation of uncertainties in approximation methods to water temperature. The input parameter solar radiation is approximated with a certain error, which propagates in the output parameter water temperature.](image)

The model sensitivity and uncertainty can be expressed with the Mean Bias Error (MBE) and the Root Mean Squared Error (RMSE). The MBE is the sum of the
differences between the measured or traditional model parameter and the modified parameter. Any positive or negative biases are observed easily with this method.

\[
MBE = \frac{\sum (I_a - I_m)}{n}
\]  

(34)

The RMSE has the advantage that it represents absolute errors by raising individual errors to squares before summation and that it stresses larger errors.

\[
RMSE = \sqrt{\frac{\sum (I_a - I_m)^2}{n}}
\]  

(35)

The RMSE and MBE were compared to the errors in the simplest statistical prediction, which is persistence. With persistence we mean that the value of the day of prediction will last for the model prediction time, so in this case that the water temperature would remain constant over the first ten days after prediction.
3 Results

3.1 Persistence prediction

The simplest statistical prediction method is persistence; we assumed that the water temperature today will last for another ten days. This gives an indication about the natural variability of the system. A persistence prediction was done for each day in the months July and August and the errors of the prediction were calculated. The error in the persistence prediction gradually increased when we moved away from the time of prediction. After ten days the RMSE was 1.7 °C in 2000 and 2.3 °C in 2003. The extreme situation in 2003 involved steeper water temperature rises and therefore the persistence prediction performed less than in the average summer of 2000.

![Error in persistence prediction](image)

Figure 7; average Root Mean Squared Error (RMSE) in predicting water temperature by assuming persistence. A persistence prediction was done for each day in the months July and August and the Bias Error (BE) of the prediction was calculated. These BE’s were averaged for the day after prediction and the square root was taken to obtain a RMSE for each day after prediction.

3.2 Inventory of uncertainties

Uncertainties can be found in the data and in the model itself (Walker, 2003). Another distinction can be made between uncertainties only involved in the forecasting model and uncertainties also involved in the hindcasting model, which are general model shortcomings. The inventory in Table 3 is not complete, but gives the most important sources of uncertainty for this modelling exercise.

Table 3; inventory of the most important uncertainties in the prediction model for water temperatures. The uncertainties are ordered in a matrix. The columns give the distinction according to the location where the uncertainties arise and the rows divide between general shortcomings and those specific for the prediction model.

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>General</strong></td>
<td>Neglecting heat exchange at river bed</td>
<td>Cooling water discharges</td>
</tr>
<tr>
<td></td>
<td>advective heat by groundwater inflow (low flow hydrology)</td>
<td>Temperature lateral boundaries</td>
</tr>
<tr>
<td></td>
<td>conductive heat</td>
<td></td>
</tr>
<tr>
<td><strong>Prediction</strong></td>
<td>Solar method approximation</td>
<td>Meteorological data</td>
</tr>
<tr>
<td></td>
<td>Discharge</td>
<td>air temperature</td>
</tr>
<tr>
<td></td>
<td></td>
<td>relative humidity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>wind speed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>air pressure</td>
</tr>
<tr>
<td></td>
<td></td>
<td>cloudiness</td>
</tr>
</tbody>
</table>
General model uncertainties involve the heat exchange at the river bed, which was neglected in the model. The advective heat transfer at the river bed is strongly influenced by low flow hydrology aspects and knowledge about low flow hydrology in the Rhine basin is little developed when compared to flood hydrology. The conductive heat transfer has not been implemented in the water temperature model. We did not evaluate friction losses and other heat exchange processes at the river bed, as we assumed these are small compared to the evaluated processes. The cooling water discharges and temperature at lateral boundaries are important sources of uncertainty in the data used for the Quick Scan model and available for the prediction model. The actual cooling water dumps may differ from the permitted dumps that are used as input to the model, especially in warm summers.

Although data on solar radiation is also limited available for hindcast models, we ordered the use of approximation methods under specific for forecast models. Where the availability of measurements is low, predictions are scarcer or may not be available at all. Discharge forecast incorporate more uncertainties than measured values used for hindcasts. Because of the long adaptation times of low flows compared to floods, low flow forecasts may be more accurate than flood forecasts. Regarding data, the main sources of uncertainties are the meteorological forecasts, which are used as an input to both the hydrological and water quality model.

The sensitivity and uncertainties were quantified with simulations with the Quick Scan model (paragraph 3.3 and 3.4). A summery of the results is given in paragraph 3.5.

### 3.3 Sensitivity of model to general uncertainties

#### Advective heat of groundwater inflow

In the previous and parallel Rhine water temperature studies (Icke, 2005 and 2006), all lateral discharges were schematized as surface water with surface water temperatures. Groundwater has a rather constant temperature of 10-12 °C, which is low compared to surface water in summer conditions.

When river discharges are low, for example 1000 m$^3$/s at Lobith, the groundwater may contribute a significant part of the water volumes. A very rough estimate of the contribution on the river branch from Koblenz to Lobith is 100 m$^3$/s (Passchier, 2006), but this value could also be 200 or 500 m$^3$/s. As the model does not take this advective heat flux into account, the water temperatures may be overestimated.

For this short error estimate we assumed that the groundwater contribution is 100 m$^3$/s and compared this coldwater flux with the warm cooling water discharges. The temperature of the surrounding water is assumed to be 20 °C. The power needed to heat the ground water on the branch from Koblenz to Lobith to this surface water temperature is approximately 4200 MW (see also equations paragraph 2.2), where the total thermal dump on the same branch equals 5800 MW. Therefore we considered the groundwater contribution significant.

#### Conductive heat to the river bed

Conductive heat to the river bed is neglected in the water temperature model. The conductive heat flux to the river bed may cause cooling of the water in spring and the beginning of the summer, when the river bed is cold. In autumn the heat flux may be of the opposite sign and the bed may supply heat to the water.
To estimate the order of magnitude of the error caused by this assumption we made an indicative calculation for a fictitious situation based on 2003 data. From the beginning of May till half June ($\Delta t = 35$ days) the water temperature rose $9^\circ C \Delta T_w$. We assumed that the temperature of a ground layer with thickness $d_g$ of 1 meter and a volumetric heat capacity $c_g \rho_g$ of 3 MJ.m$^{-3}$.K$^{-1}$ also raised $9^\circ C$ over this period. The heat flux to the ground layer $q_g$ is then approximately 9 Watt.

$$q_g = \frac{\Delta T c_g \rho_g d_g}{\Delta t} \quad (36)$$

We further assumed that this heat is withdrawn from the water column and that the water stays for 10 days $t_s$ in the basin. The change in water temperature for water with a depth $d_w$ of 6 meters was calculated with:

$$\Delta T_w = \frac{q_g t_s}{d_w \rho_w c_w} \quad (37)$$

The value found is 0.3 $^\circ C$ and is linear dependent on the water depth and more important on the thickness of the ground layer, which is unknown. The calculation is very simplified, but just meant to estimate the order of magnitude of the flux. The conduction depends for example also on the temperature difference between the ground and the water. Another simplification is the contact surface, which may be larger than the horizontal surface, because of infiltration and large pores in the bed material.

**Cooling water discharges**

The actual cooling water discharges may differ from the permitted values, especially in warm summers. Energy producers change from discharging cooling water on the river to cooling towers. Moreover the general production level may be lower. For the summer of 2003 reports were found that power plants in southern Germany had to limit their production to 80 % of full capacity, whereas plants in the Ruhr region had to go back to a production level of 50 % (Neue Energie, 9/2003).

Table 4; examples of power reduction of plants in Germany in August 2003 (Neue Energie, 9/2003).

<table>
<thead>
<tr>
<th>Plant</th>
<th>Location</th>
<th>Power reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voerde Duisburg</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>Walsum Duisburg</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>Phillippsburg Mannheim</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>Neckarwestheim Block I Stuttgart</td>
<td>20</td>
<td></td>
</tr>
</tbody>
</table>

For model purposes, the restrictions of the European fish water directive (78/659/EEC) could be assumed. However the standards in this directive may be exceeded in crises situations. In August 2003, Rhine water temperatures reached 30 $^\circ C$, where 28 $^\circ C$ was allowed.

Icke (2005) ordered the thermal dumps into three river branches, higher, middle and lower Rhine. If we increase the thermal dump in one of the two downstream river branches at Koblenz or near Lobith with 1600 MW, which is about the power of the plants near Nijmegen, we see only minor temperature rises in Lobith of 0.2 to 0.3 $^\circ C$. Increasing thermal dump at Rekingen in the higher part of the basin showed no effect on model results.
Temperature lateral boundaries

Measurements were not available for all lateral boundaries. As the timescales of the heat fluxes (paragraph 2.2) are smaller than the length of stay of the water from the boundaries to Lobith, the model sensitivity to water temperatures at the boundaries was expected to be small. The influence of water temperature set at the upper Rhine and Aare boundaries can indeed be neglected and also the discharge implemented on these boundaries showed very little effect on Lobith water temperatures. Changing the temperature of lateral discharges in the upper Rhine (Reckingen) had no influence, but the lateral discharges between Mannheim and Lobith (in figure Koblenz and Lobith) logically had. Still the model was not very sensitive to changes; a temperature rise of 5 °C in the lateral discharges between Cologne and Lobith would result in approximately 1 °C temperature rise at Lobith.

Figure 9; sensitivity of Lobith water temperature to changes in water temperature of lateral discharges. The water temperature was raised with 1 and 5 °C in higher Rhine (Reckingen), Middle Rhine (Koblenz) and Lower Rhine (Lobith).
3.4 Propagation of uncertainties specific for forecast model

Discharge
The hydrology and hydrodynamics of the Quick Scan model was very simplified. Though discharge forecast in a low flow situation may be easier than in a flood situation, we may expect uncertainties in the discharge forecasts. Therefore we tested the model sensitivity to discharge variation. When discharges are smaller, the dilution of cooling water dumps may be smaller. Moreover, would the flow velocities decrease and therefore the length of stay in the basin increase. The influence of discharge variations as such are however limited as can be deduced from Figure 10. This may be explained by the time scales of the heat exchange processes (see paragraph 2.2). The transit time between the location of large cooling water discharges in the model and Lobith is larger than these timescales and therefore the dilution and length of stay effects may be small. The variation of discharge may have significant influence if the water temperature differences are higher, which was evaluated in the previous paragraph for groundwater inflow.

![Lobith water temperature: sensitivity to discharge.](image)

Figure 10; sensitivity of the model outcome to discharge variation at the boundaries of the higher Rhine. The sum of the discharges at the upper boundaries (Aare and Bodensee) was reduced with 200 m$^3$/s.

Solar method approximation
Solar radiation measurements and predictions are scarcely available; therefore a prediction model might have to use approximation methods. There are different solar radiation approximation methods available as presented in paragraph 2.4. These methods were compared in Table 5 that shows that all methods have a relative large positive bias when compared to the RMSE. Calibration for summer months may therefore increase the performance of the methods. The Ångström-Prescott method showed best fit for the data at the Bilt, but sun hours are not available in the standard data packages distributed by Germany’s National Meteorological Service (DWD, Deutsche Wetterdienst). For further analysis we therefore used results of the Gill method.
Table 5: comparison solar radiation approximation methods. Errors over the period June till September 2000 when compared to measurements at de Bilt. The percentage is the error compared to the average radiation in these months, which is 14.45 MJ.m$^{-2}$.

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
<th>MBE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MJ.m$^{-2}$</td>
<td>% MJ.m$^{-2}$</td>
</tr>
<tr>
<td>Ångström-Prescott</td>
<td>3.09</td>
<td>21</td>
</tr>
<tr>
<td>Hargreaves</td>
<td>4.16</td>
<td>29</td>
</tr>
<tr>
<td>Supit</td>
<td>8.53</td>
<td>59</td>
</tr>
<tr>
<td>Gill, Ag Gill, wind Sweers</td>
<td>3.67</td>
<td>25</td>
</tr>
<tr>
<td>Gill, Ag, Gill, wind Gill</td>
<td>3.52</td>
<td>24</td>
</tr>
<tr>
<td>Gill, Ag Ludikhuize, wind Sweers</td>
<td>3.91</td>
<td>27</td>
</tr>
</tbody>
</table>

The error caused by approximation of solar radiation may result in an error in water temperatures. Because of the positive bias in the approximation method the effect in on water temperature accumulated to a maximum of 0.4 ºC after ten days (Figure 11).

![Propagation RMSE approximation solar radiation to RMSE water temperature](image)

Figure 11: propagation of the error in solar radiation approximation to water temperatures. Predictions were simulated six times in the period July, August 2000. The RMSE was calculated out of the MBE for each day after prediction.

**Meteorological predictions**

The uncertainty of an air temperature prediction issued by KNMI is illustrated in Figure 12. Based on a set of similar graphs we assumed an error, which increased to a value of 1.3 ºC after nine days as shown in Figure 13. The effect on water temperature is small the first few days after prediction but gradually increases to 0.2 ºC after nine days.
No graphs with confidence bands could be found for relative humidity, which is an important factor in the evaporation process. The values for relative humidity in the July and August 2000 ranged from 55 to 100% and based on this range we assumed an increasing error to 15% after nine days. This resulted in an error in water temperatures of 0.5 °C.
Wind speed is the only discussed parameter that directly influences both the processes HEATBAL and EXESS. Because of technical model deficiencies, it was not possible to vary the wind speed error with time. Change of the absolute value resulted in significant temperature changes; a wind speed difference of 1 meter per second may result in 1 to 2 °C temperature difference at Lobith for the natural temperature NatTemp and another 0.5 °C for the surplus temperature ModTemp. The width of the KNMI confidence bands for wind speed is approximately 1 m.s\(^{-1}\) for summer conditions.

Figure 14: propagation of error in relative humidity to water temperatures. Predictions were simulated six times in the period July, August 2000. The RMSE was calculated out of the MBE for each day after prediction.

Figure 15: sensitivity of the background temperature NatTemp to wind speed.
Lobith modified water temperature: sensitivity to wind speed.

Figure 16; sensitivity of the surplus temperature ModTemp to wind speed.

The model showed very little sensitivity to changes in air pressure and cloud cover. Errors in cloud cover may however propagate in the model due to the use of these data in the solar radiation approximation. The method is sensitive to errors in cloud cover predictions with errors up to 0.9 °C.

Figure 17; propagation of error in cloud cover predictions via solar radiation approximation method to water temperatures. A cloud cover with an assumed prediction error was used as input for the radiation approximation.
3.5 Summary of the results

Table 6 summarises the results of the sensitivity and uncertainty analysis. For all sources of uncertainty, except for low flow hydrology, a qualitative indication of the sensitivity is given. Where possible a quantitative error estimate is given. These values rely on many assumptions and serve therefore only indicative purposes. The advective heat flux from groundwater inflow, the wind speed and the radiation, approximated with cloudiness, seem to be the largest sources of uncertainty. These factors thus require most attention in model exercises concerning water temperature.

Table 6; summary of the sensitivity and uncertainty analysis. All values in the table are in °C water temperature. For most uncertainties a qualitative sensitivity is shown in the second column. Where possible a time dependent estimate of the uncertainty is given or for some uncertainties a time independent estimate.

<table>
<thead>
<tr>
<th>Uncertainty</th>
<th>Sensitivity</th>
<th>RMSE in time [days]</th>
<th>RMSE estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low flow hydrology</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neglecting heat exchange at river bed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>advective heat by groundwater inflow</td>
<td>high</td>
<td></td>
<td>-2</td>
</tr>
<tr>
<td>conductive heat</td>
<td>moderate</td>
<td></td>
<td>-0.3</td>
</tr>
<tr>
<td>Cooling water discharges</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South Germany</td>
<td>low</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle Germany</td>
<td>low</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Germany</td>
<td>moderate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature lateral boundaries</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South Germany</td>
<td>low</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle Germany</td>
<td>low</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Germany</td>
<td>moderate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar method approximation</td>
<td>moderate</td>
<td>0.2 0.2 0.2 0.2 0.2</td>
<td>0.3 0.3 0.3 0.4 0.4</td>
</tr>
<tr>
<td>Meteorological data</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>air temperature</td>
<td>moderate</td>
<td>0.0 0.0 0.0 0.1 0.1</td>
<td>0.1 0.1 0.2 0.2 0.2</td>
</tr>
<tr>
<td>relative humidity</td>
<td>moderate</td>
<td>0.0 0.1 0.1 0.1 0.2</td>
<td>0.3 0.4 0.5 0.5 0.5</td>
</tr>
<tr>
<td>wind speed</td>
<td>high</td>
<td></td>
<td>-2</td>
</tr>
<tr>
<td>air pressure</td>
<td>low</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cloudiness</td>
<td>high*</td>
<td>0.2 0.3 0.3 0.3 0.4</td>
<td>0.5 0.6 0.7 0.7 0.9</td>
</tr>
</tbody>
</table>

* This is the combined influence of cloudiness and solar radiation approximation.
4 Discussion

Kooiman (2004) suggested that short term prediction could enable the energy sector to adapt production levels. From a water manager point of view adapting production levels may be seen as a measurement to reduce surface water temperatures. This study showed that such measures have an effect on the water temperature, but that the required reductions are large and only show significant effect, if applied on the river branches downstream of Koblenz. A similar result was later found by Icke (2006). He concluded that the removal of cooling water discharges in middle Germany (from Mainz to Koblenz) would only result in a 1ºC water temperature difference at Lobith. A 50% reduction between Koblenz and Lobith resulted in a 1ºC temperature reduction. Even if the effect of reduction measures is small, predictions may still be valuable for the energy sector, as the high water temperatures may reduce system efficiency.

The sensitivity of the temperature model to changes in the meteorological conditions was also found by Icke (2003). Consistent with our research, Icke (2003) found that the temperature model was sensitive to radiation, wind speed and relative humidity and that air pressure had little influence. For the Meuse Icke (2003) for example found that a radiation increase of 25% led to a maximum water temperature difference of 2 ºC in summer. This 25 % is comparable to the error of the approximation method used in this research but we found a smaller water temperature deviation of 0.4 ºC after ten days. This may partly be explained, because the evaluated period was shorter, 10 days instead of a season for the Meuse case. Moreover the influence of radiation may be larger, because the Meuse is a shallow river with small flow velocities, when compared to the Rhine in summer conditions.

The assumption to neglect groundwater influences seems incorrect. The contribution of the advective heat flux caused by cold groundwater to water temperatures is significant, as shown in indicative calculations. While calibrating the Rhine water temperature model, Icke (2006) found that modelled water temperatures were 2 to 3 ºC higher than the measured values at Lobith. This difference may partly be explained by the missing groundwater flux in this model.

The uncertainties in the analysed model instrument are large and the accumulated errors may even exceed the errors in the persistence prediction. Although the results of the uncertainty and sensitivity analysis rely on many assumptions, they form a strong indicator that model improvements or another modelling approach is necessary to forecast water temperature with added value. We argue that design of a forecast or warning model should not always be close to the hindcast model for the same situation. Knowledge acquired with studying the system and possibly making a hindcast system could be used to design a system for forecast purposes.
5 Conclusions and recommendations

5.1 Conclusions
We may conclude that the skill of forecasts issued with the suggested water temperature model is small. Reasons for this small skill are on the one hand the small variations in Rhine water temperatures in summer and on the other hand the large uncertainties in the model and the input parameters. Part of the uncertainties is caused by general model deficiencies, which are not specific for forecasting, such as the neglecting of groundwater fluxes. But even if the model is improved, the uncertainties in weather forecasts used as model input are significant and may reach values close to the natural variability of the system.

The characteristic timescale of the heat exchange processes was estimated between 0.5 and 2 days. Therefore large influence factors on the Lobith water temperature could geographically only be found downstream of Koblenz. Also the shifting of high water temperatures caused by thermal discharges from upstream to Lobith seems limited to the lower parts of the River Rhine. The influence of changes in cooling water discharges in the higher and middle part on Lobith water temperatures is small and reducing dumps with 25% between Koblenz and Lobith may only lead to 0.3 °C water temperature difference at Lobith. Because meteorological conditions are dominant over thermal dumps, no large water temperature reductions on basin scale may be expected by human intervention within a 10 day time scope.

5.2 Recommendations
It may be clear from the sensitivity analysis and the conclusions that the added value of a water temperature prediction with the suggested system compared to the assumption of persistence is small. However, this is also often the case for meteorological forecast, which are widely accepted, and there is a market demand for water temperature predictions. With WL|Delft Hydraulics FEWS technology, it is (with some adaptations) technically feasible to provide water managers and energy sector with water temperature predictions. WL|Delft Hydraulics could therefore accept the uncertainties in the meteorological forecasts and pursue a water temperature modelling approach that adds as little uncertainties as possible.

In order to achieve this, it is first recommended to improve the hydrology of the water temperature model:
- Add a more realistic hydrologic and hydrodynamic model to the water temperature model based on FEWS|NL.
- Pay special attention to the groundwater inflow and whether this inflow is well approximated with the HBV model. Quantify the groundwater flux for low flow conditions. This could be done by an analysis of isotopes or conservative chemical components in the summer Rhine discharges and the tributaries.
- Analyse the other heat exchange processes at the river bed.

With the improved hydrologic and hydraulic model the water temperature could be tested again in hindcast situation. The obtained model could be used for policy analysis, discharge permissions and climate change impact studies.
As a second step specific for forecasts, we recommend to adapt the water temperature formulations in DELWAQ in such a way that less meteorological input parameters are required. Especially a formulation without radiation would better serve forecasting purposes. With for example generic programming or another data driven approach a more simple relationship for water temperatures in the River Rhine might be found. Formulations could be similar to Sweers (1979), which is already used in the DELWAQ cooling model. Other references on more simple water temperature formulations include Caissie (2005), who suggest an equilibrium temperature concept, and Mohseni (1999), who elaborated on the s-shaped relationship between air temperature and water temperature. Because of this s-shaped relationship the water temperature formulations do not necessarily have to be constant during the whole year.

The influences of cooling water discharge reduction on the basin scale may be small, still reduction in extreme situation may be necessary to protect the aquatic life near power plants. Further research on the local effects of thermal dumps on aquatic life especially in extreme situations is recommended.

A last recommendation follows from the conclusion that ten day predictions do not give many possibilities for measurements that reduce the water temperature on basin level, but longer lead forecasts may give possibilities. It is recommended to study possibilities for seasonal forecast of Rhine water temperature, as this has more added values for policy makers and the energy sector. The energy sector can decide to buy energy abroad, if a summer with cooling water scarcity is expected.
Part B:

Forecast of summer Rhine cooling water limitations from preceding winter oceanic and atmospheric patterns

a feasibility study for statistical modelling approach using linear regression and pattern recognition techniques
Abstract
Based on the results of a correlation analysis, linear regression models were derived to forecast summer Rhine water temperatures and discharge with large scale oceanic and atmospheric patterns. The linear regression models containing North Atlantic and Arctic Oscillation indices showed best overall performance. The correlations $r$ between the forecast and the response over the test period were 0.4 for July water temperatures, 0.5 for August water temperatures, 0.2 for July discharges and 0.5 for August discharges. The August water temperatures were best predicted with a model containing principle components of the correlated sea surface temperature field in February.
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List of abbreviations

AO Arctic Oscillation
BADC British Atmospheric Data Centre
DWD Deutsche Wetterdienst (Germany’s National Meteorological Service).
ECMWF European Centre for Meteorological Weather Forecasts
ICOADS International Comprehensive Ocean and Atmospheric Data Set
KNMI Koninklijk Nederlands Meteorologisch Instituut (Dutch Royal Meteorological Institute)
MBE Mean Bias Error
NOA North Atlantic Oscillation
NOAA National and Atmospheric Administration (United States)
PC Principle Component
PCA Principle Component Analysis
RMSE Root Mean Squared Error
RIZA Rijksinstituut voor Integraal Zoetwaterbeheer en Afvalwaterbehandeling (Dutch Institute for Inland Water Management and Waste Water Treatment)
SST Sea Surface Temperatures
SSTA Sea Surface Temperature Anomaly
SVD Singular Value Decomposition
SUN Sunspot number
UKMO United Kingdom Meteorological Office
Z500 500hPa geopotential heights
1 Introduction

Seasonal early warning for cooling water problems could for example enable the energy sector to buy energy abroad or the authorities to setup awareness campaigns. The Dutch Institute for Inland Water Management and Waste Water Treatment (Rijksinstituut voor Integraal Zoetwaterbeheer en Afvalwaterbehandeling, RIZA) issues drought reports. The first drought report is published every year in the beginning of April and can therefore be seen as a seasonal forecast. In this drought report RIZA compares the actual situation for drought indicators with long year average values and gives qualitative remarks on chances of drought occurrence in summer. The drought indicators RIZA uses are the traditional water balance components: the precipitation in the Netherlands over the winter months, the snow cover in the River Rhine Basin, the water level of the Lake of Constance, the Rhine and Meuse discharges and an experimental long term weather forecast from the Dutch Royal Meteorological Institute (Koninklijk Nederlands Meteorologisch Instituut, KNMI). The RIZA drought report mainly focuses on the low flows with a small hint to temperatures.

Recent research investigated the possibilities for drought forecasting in Europe with empirical statistical models that use winter large scale oceanic and atmospheric patterns as predictors. The slow timescale of variation in the large scale oceanic and atmospheric circulation system would make those good predictors for seasonal forecasts. Johansonn (1998) examined the forecasting skill of large scale pattern for air temperature and concluded that most of the skill origins from geopotential height fields. Winter North Atlantic Ocean temperatures are used as predictors for summer temperature rainfall and pressure in Europe by Colman (1999). His findings form the basis for seasonal forecasts issued by the Met Office. Wedgbrow (2002) has shown that relationships between large scale North Atlantic climatic indices and summer flow of rivers in Wales and England exist. Models for seasonal predictions of summer hydrometeorology of the River Thames using lagged relationships with wintertime sea surface temperatures, sea ice extent and atmospheric circulation patterns have been derived by Wilby (2004). The skill of these models is moderate, but still higher than physical models of the European Centre for Medium-Range Weather Forecasts (ECMWF) on which also KNMI bases her seasonal forecast.

The purpose of this research is to assess the skill of winter large scale atmospheric and oceanic patterns as predictors for Rhine summer cooling water problems. It investigates whether these patterns could provide useful information for water mangers and the energy sector about the chances of drought occurrence. Applications of such seasonal forecasts are of course wider than this cooling water problem. Also agriculture and shipping industry could for example benefit from seasonal low flow and drought forecasts.

Taking into account the Dutch standards, monthly average water temperatures over 23 ºC are a strong indicator for cooling water problems. A seasonal prediction of chances of exceedance of this limit would therefore be interesting, especially if discharge, the second limiting factor to cooling water usage, can also be estimated. As discharge is only a second limiting factor, estimating a lower boundary below which problems occur is more difficult. The Dutch crises team for water distribution (Landelijk Coordinatiecentrum Waterverdeling, LCW) uses a lower boundary of 1200 m$^3$/s for July and 1100 m$^3$/s with a minimum duration of three days (RIZA, 2005).
In this research a correlation analysis was executed to explore the strength and stability of the relationships between large scale atmospheric and oceanic patterns and Rhine summer water temperatures and discharge. Therefore parameters that describe the large scale atmospheric and oceanic circulation were chosen based on recent publications. The correlation analysis used principle components to reduce the information contained in fields. Multiple linear regression models were derived with the significantly correlated parameters as predictors. These parameters were atmospheric indices, principal components or expansion coefficients resulting from Singular Value Decomposition.
2 Material and methods

2.1 Parameters

2.1.1 Responses

A predictor is a parameter that contains skill to forecast the parameter of interest, the response. As response we used monthly averaged water temperature and discharge for the months July and August at Lobith just across the German border, where the River Rhine enters the Netherlands. Figure 1 shows the summer water temperatures at this location over the last century. The summers of 1994 and 2003, when cooling water was scarce, are clearly visible with their average water temperatures over 23 °C. We observe a gradual increase of average water temperatures from 1910 till 1940 and again from 1970 till present. These increases may be partly explained by an increase of water use for industrial and to a lesser extent domestic purposes. Another influence factor, which has especially been important over the last decades, is climate change. The period of the stagnation of the rise in Figure 18 seems to correspond with the short ice decades, which Europe experienced after the Second World War until the 1970s (Kroonenberg, 2006).

The summer discharges have shown no significant increasing or decreasing trend over the last century. For the River Rhine a discharge lower than 1100 m$^3$/s is considered low. The driest month of the year is not July or August, but October (de Bruijn, 2006). Minimum discharges over the summer months are observed for the dry summers of 1976 and 2003 (Figure 2). Discharges in July and August seem highly correlated, where the discharge in August tends to be lower than the discharge in July.
2.1.2 Predictors

Summer high water temperatures and low flows may be forecasted with large scale oceanic and atmospheric patterns in winter or indices describing the strength off the patterns. The long adaption times of changes in these patterns may make them skilful predictors for seasonal forecasts. The choice for predictors resulting from atmospheric and oceanic patterns was based on research by Johansson (1998), Colman (1999) Wedgbrow (2002) and Wilby (2004). A third low frequency phenomenon that has often been associated with longer term forecasts is the sun cycle or the sunspot number. Though we used statistical models in this research, qualitative examples of physical relationships are given as an introduction.

Pressure fields

Pressure fields are an indicator for the state of the atmosphere (Johansson, 1998). With pattern recognition techniques as Principal Component Analysis (see also paragraph 2.4), indices have been derived to describe important modes of variability in the global pressure fields. An important pattern for European climate conditions is the stable combination of a high pressure field above the Azores and a low pressure field above Iceland. A large pressure difference causes stronger western winds above the North Atlantic for the mid latitudes, resulting in stormy and wet winters in northern Europe and dry conditions in central and southern Europe (Tallaksen, 2005), whereas the opposite is the case when pressure differences are small.

In the 1920s Sir Gilbert Walker identified the pressure difference at sea level between the Azores and Iceland as important mode of climate variability in the North Atlantic. Several indices were defined expressing the strength of this pressure difference of which the North Atlantic Oscillation Index is the best known. The North Atlantic Oscillation Index is the dominant pattern over the North Atlantic Ocean. The United States’ National and Atmospheric Administration (NOAA) publishes more indices that describe the variability of atmospheric pressure fields of which the Artic Oscillation Index was also used as predictor in this research. The Artic Oscillation is the dominant pattern of non-seasonal sea-level pressure variations north of the ring of Cancer and is related to the strength of the westerlies similar to the North Atlantic Oscillation Index.
Figure 20: Examples of the influence of the North Atlantic Oscillation Index on the western European climate conditions. The left picture shows how a high pressure field above the Azores in combination with low pressure field above Iceland causes stronger storms over the North Atlantic, resulting in above average precipitation in North western Europe, whereas South Europe experiences dryer climate conditions. The right picture shows the opposite case (source: http://ido.columbia.edu/NAO).

The North Atlantic Oscillation and the Arctic Oscillation may describe the most important modes of climate variation; other patterns may be a good predictor for our specific responses. After Johansson (1998) we used the 500 hPa geopotential height (Z500) fields to search for such patterns. Geopotential heights are the location of the 500 hPa pressure levels above mean sea level.

**Sea surface temperatures**

The used indicator for oceanic patterns is sea surface temperatures. An example of a recognisable pattern in sea surface temperature is the Gulf Stream, which transports warm water towards the north western European coast. Above average sea surface temperatures towards the west of the Atlantic in winter may result in above average summer land and water temperatures in our regions. If the sea surface temperatures of the North Sea and Western part of the Atlantic Ocean are high in winter, the evaporation is large and therefore precipitation in the Alps may be above normal. A large part of the Rhine discharge in summer results from snow melt, so high winter precipitation reduces the chance of low flows.

Colman (1996) identified a winter sea surface temperature pattern that has since been used by the UK Meteorological Office for forecasting of summer western Europe air temperatures, including the Netherlands. Values for this pattern were not available for this research. For sea surface temperatures we therefore only used the complete field information to search for pattern and no comparison with an index was possible.
Figure 21: Sea surface temperature anomalies for January 2006. In large parts of the North Atlantic the Sea Surface temperatures were above average conditions. The water of the Mediterranean Sea was cooler than normal (source http://www.cdc.noaa.gov/cdc/data.kaplan_sst.html).

Sunspots
A sunspot is a dark part of the sun surface that is cooler than the surrounding surface. The amount of sunspots is not constant; their number of appearance increases and decreases on a regular cycle between 9 and 11.5 years. Even though sunspots are cooler than the rest of the sun surface, their number is positively associated with solar activity. Solar activity may influence the climate on earth. Araya (1999) for example found that the frequency peaks for solar data coincide with climate data of Central America. Dettinger (1995) used solar spots as a parameter in relationship to surface temperatures in the United States. Spier (2000) speculated about a relation between a small number of sun spots and enough winter ice to skate the ‘Elfstedentocht’. Reasoning along this line we may postulate that a large number of sun spots could be an indicator for hot summers.
2.1.3 Data sources
The used data were obtained from free sources. We were especially interested in model behaviour for warm and dry summers, therefore only datasets containing the dry and warm summers of 1976, 1994 and 2003 were used.

For response parameters, water temperature (WT) and discharge (Q), we chose measurements at Lobith. High water temperatures and low flows at Lobith are a strong indicator for cooling water problems along all inland waterways in the Netherlands. Monthly averaged values for the summer months July (7) and August (8) were used. Figures were obtained from RIZA and covered 1909 to 2004 for water temperature and 1900 to 2004 for discharges.

The predictors were monthly average values over the months January (1), February (2) and March (3). For the North Atlantic Oscillation (NAO) and the Arctic Oscillation Index (AO) records from NOAA covering the period from 1950 till present were used. After Johansson (1998) the 500 hPa geopotential height field (Z500) was taken as parameter for atmospheric pressure fields. The data were obtained from the United Kingdom Meteorological Office (UKMO) and hold gridded (5° latitude by 10° longitude grid) Northern Hemisphere monthly series. The data was available for the period 1945 to 2004. For sea surface temperature (SST) we used the Kaplan Sea Surface Temperature Anomaly (SSTA) set. The Kaplan SSTA data is based on the global sea surface temperature record collected by the UKMO and was derived from the earlier MOHSST5 data. Sea surface temperatures were available from multiple data sources for different grid sizes. We choose the Kaplan SSTaA, above the data from the International Comprehensive Ocean Atmospheric Data sets (ICOADS) and UKMO HADISST. ICOADS and HADISST contained more missing values and the grid size was smaller, which would imply more computations.

Table 7; used data sources. The sources are RIZA, the British Atmospheric Data Centre (BADC) and the National Oceanic and Atmospheric Administration (NOAA) of the United States Department of Commerce. Grid values are given as degrees latitude by degrees longitude.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Source</th>
<th>Name data set</th>
<th>Temporal coverage</th>
<th>Spatial coverage</th>
<th>Grid</th>
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<td>WT</td>
<td>RIZA</td>
<td></td>
<td>1909-2004</td>
<td>Lobith</td>
<td></td>
</tr>
<tr>
<td>Discharge</td>
<td>Q</td>
<td>RIZA</td>
<td></td>
<td>1900-2004</td>
<td>Lobith</td>
<td></td>
</tr>
<tr>
<td>Sea Surface Temperature</td>
<td>SST</td>
<td>NOAA</td>
<td>Kaplan Extended SST V2</td>
<td>1856 to present</td>
<td>Global</td>
<td>5 by 5</td>
</tr>
<tr>
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<td>NAO</td>
<td>NOAA</td>
<td>Kaplan Extended SST V2</td>
<td>1856 to present</td>
<td>1950 to present</td>
<td></td>
</tr>
<tr>
<td>Arctic Oscillation</td>
<td>AO</td>
<td>NOAA</td>
<td></td>
<td>1950 to present</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pacific North American</td>
<td>PNA</td>
<td>NOAA</td>
<td></td>
<td>1950 to present</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geopotential heights</td>
<td>Z500</td>
<td>BADC</td>
<td>ukmo-height</td>
<td>1945-2004</td>
<td>Northern Hemisphere</td>
<td>5 by 10</td>
</tr>
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<td>Number of sunspots</td>
<td>SUN</td>
<td>NOAA</td>
<td>sunspot-numbers</td>
<td>1749 to present</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.2 Time-series analysis and data preparation
Water temperatures in July and August have shown a significant increasing trend over the last century. This trend is partly caused by an increase of water use for cooling purposes; a disturbance which is not likely to be found back in the large scale patterns used as predictors. Two other problems may arise due to trends. First if the response and predictor both contain a similar long term trend, the correlation values may be high, but the skill of this predictor in seasonal forecast can be small. The second problem may arise while using jack knife techniques for testing, because models are trained against time-series with broken trends. Where water temperatures have shown
a clear increasing trend over the last century, the average summer discharges have been quite stable. Discharges in August have shown a small decreasing trend and there has been no visible trend in July discharges.

We chose to remove the trend from the data with a moving average filter (Baptist, 2000). A moving average filter removes a (weighted) average of a certain period from the data. The window is determined by three parameters location, width and shape as illustrated in Figure 22. Only a one sided left window can be used for forecasting purposes, whereas the centred and right window use ‘future’ data. The choice of the width of the time window is important, because a too small window may remove important information from the data, whereas a too large window may not remove the trend. With alternative shapes such as triangles and sinus, more importance can be given to data close to the point of interest.

\[ x_t = A(0) + \sum_{k=1}^{q/2} \left( A(k) \cos(w_t) + B(k) \sin(w_t) \right) \]  

The first estimate of the width and shape of the moving average window was determined with a Fourier analysis. A Fourier analysis dissolves a time-series of length \( n \) in series of sinus and cosines functions with different frequencies \( w_k \) and amplitudes \( A \) and \( B \).

The amplitudes \( A(k) \) and \( B(k) \) are a measure for how strong the accompanying frequency \( w_k \) is present in the time-series. The spectrogram that is obtained with a Fourier analysis contains information about parameter behaviour. Clear peaks in this spectrogram may indicate cyclic behaviour. The high peaks with return periods \( k \) close to halve of the evaluated time-series can not be trusted as indicators for cyclic behaviour over the evaluated period, but are indicators for long term trends.

A well-chosen moving average filter would remove these long term trends and therefore the large amplitudes for periods close to half of the length of the time-series. The Fourier analysis resulted in a first estimate for the window width and shape. By adjusting the width and shape model performance could be improved.
2.3 Linear correlation analysis

2.3.1 Procedure

From the population of parameters, predictors had to be selected. In this paragraph the process to select predictors and give an estimate of the total combined correlation of all analysed fields is outlined. Detailed descriptions of the italic printed techniques can be found below.

A first test whether a parameter is suitable for prediction purposes is correlation analysis. A simple correlation linear correlation analysis was executed for the atmospheric indices, including the sunspot numbers and the time-series at the grid points in the sea surface temperature and geopotential height fields.

The large number of grid points in the sea surface temperature fields and the geopotential height fields would make further analysis difficult. Large interdependencies were expected between the time-series. Moreover would calculation of the multiple correlation not be possible, because the total of correlated parameters would exceed the number of years in the time-series. Therefore we reduced their number by deriving sets of orthogonal patterns and expansion coefficients with the derivation of Principal Components (PC). In this way most skill of the fields was concentrated in one or few orthogonal time-series.

Some indices that were significantly correlated to the response were not only significantly correlated for the winter previous to the response, but also for longer lag times. If this was the case, again Principal Component Analysis (PCA) was used to find the PC out of the field of time-series for different lag times.

Figure 23; structure diagram which shows how parameters were reduced to a maximum correlation estimate of all predictors for the response.
By calculating the *multiple linear correlations* of the significantly correlated PC and indices, an estimate for the maximum correlation of the combination of indices and field predictors was made. The skill of a predictor however not only depends on correlation, but also on the temporal and for fields the spatial stability as well. The stability was evaluated at different stages in the correlation analysis by dividing the time-series in two equal parts and comparing the two correlation figures and in case of fields the correlation patterns.

### 2.3.2 Correlation analysis

Correlation analysis is a statistical tool that can be used to describe the degree to which one variable is linearly related to another. Though not all coherence between two data series can be reproduced under the assumption of linearity, we believe that if parameters show no linear correlation chances are very small that there is any other correlation. The correlation coefficient indicates the strength and direction of a linear relationship between two parameters. The Pearson product-moment correlation coefficient used in this research is obtained by dividing the covariance of the two variables by the product of their standard deviations.

To evaluate the significance of the results we compared results to the null-hypothesis by calculating the so called p-value. The p-value is the probability that the current result would have been found, if the correlation coefficient was in fact zero. The level to which results are considered significant can depend on the area of research, supportive evidence or expectations. We adopted two levels of significance that are used by Wedgbrow (2002), the 0.05 and the 0.01 level, meaning that chance that the found correlation is a coincidence is respectively less than 5% and 1%. In general research practise, results that yield 0.05 are considered borderline statistically significant, results that are significant at the 0.01 level are considered statistically significant.

### 2.3.3 Principle Component Analysis

Principle Component Analysis (PCA) is similar to the calculation of eigenvalues. PCA is equal to Empirical Orthogonal Function (EOF) transformation. It is a powerful tool to reduce multiple dependent parameters to one or few parameters which explain most of the total variance. PCA can be explained with a simple example of two parameters $X_1$ and $X_2$ in Figure 7, taken from Tallaksen (2005). From the original series $X_1$ and $X_2$ a PCA produces $PC_1$ and $PC_2$. The principle components or axes are orthogonal and $PC_1$ explains the largest proportion of variance in the dataset.
The SST and Z500 time fields that were selected with linear correlation analysis were large and contained many dependencies. With PCA their number was be reduced to a small set of independent time-series of patterns. A pattern or principle component can be viewed as a map of contour lines and the accompanying time-series, called expansion coefficient, shows the oscillation of this pattern in time. The variability of a field can in most cases be recovered with a limited number of patterns and expansion coefficients, when compared to the number of grid points. Below we give a brief introduction to the method, for a complete description we refer to Preisendorfer (1988). The manual by Björnsson (1997) gives a practical description of Empirical Orthogonal Function transformation, which is equal to PCA.

Let us start with a matrix, $s(n, T)$ containing predictor data, e.g. SST in January. The data in this matrix can be approximated with a set of spatial orthogonal patterns, $p_k$, and expansion coefficients, $a_k$.

$$\tilde{s}(t) = \sum_{k=1}^{n} a_k(t) p_k$$  \hspace{1cm} (39)

The patterns are the eigenvectors of the covariance matrix of $s(n, T)$ and each eigenvalue is a measure for the amount of variance explained by the accompanying eigenvector. The $k^{th}$ expansion coefficients can be found by projecting the matrix $s$ onto the $k^{th}$ pattern.

$$a_k(t) = \sum_{i=1}^{n} p_k s_i(t)$$  \hspace{1cm} (40)

As the patterns are orthogonal, EOF expansion coefficients are independent.

### 2.3.4 Multiple linear correlation

The estimate for the multiple linear correlation was calculated with a multiple linear regression equation. This equation relates multiple predictors, $x_1...k$, to the response, $y$:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \varepsilon$$  \hspace{1cm} (41)

Where $\beta_0...k$ is a set of linear coefficients and $\varepsilon$ is the remaining error.
2.4 Forecast models

2.4.1 Procedure

With the correlation analysis possible predictors were identified. This paragraph discusses the derivation of models containing these possible predictors. Four series of models were derived. The first series contained indices. The indices were related to the response with one variable or multiple variable linear regression equations. The predictors were selected out of the significantly correlated parameters with forward selection. The other series also used linear regression equations. The parameters in the second series were expansion coefficients resulting from PCA of the correlated sea surface temperature or geopotential height field. In the third series we used expansion coefficients of Singular Value Decomposition (SVD), a technique similar to PCA, which is further described below. The fourth series of models combined the expansion coefficients of fields with indices as input for the multiple linear regression model. All models were tested in a 'pseudo operational context' and evaluated on the performance indicators correlation, bias error root mean squared error and true sign forecasts. Results were presented with 'inflated' regression.

Figure 25: procedure followed in model derivation. With help of principle components and singular value decomposition three series of models were derived.
2.4.2 Singular Value Decomposition

Where EOF finds patterns under the condition that the field covariance is maximized, Singular Value Decomposition (SVD) finds patterns while maximizing the cross covariance to another field. Bretherton (1992) is a good reference for a more complete description of SVD. In this text SVD is used to refer to the methodology, whereas the complete name singular value decomposition is used to refer to the matrix operation as such. SVD is a method to find coupled spatial patterns in two data fields, with each pair explaining a fraction of the covariance between the two fields. With SVD, the data in one field is reduced to one vector to allow for correlation analysis to the other field. Similar to EOF, this would result in sets of spatial patterns and expansion coefficients. In this case we analysed the behaviour of a vector and a field and the correlation can be explained by one pattern and one expansion coefficient, because of the many degrees of freedom each pattern has.

Let us start with a matrix, \( s(n_s,T) \) containing predictor data, e.g. SST in January and a vector, \( z(1,T) \), containing response data, e.g. July water temperatures. The matrix can again be approximated with a set of spatial orthogonal patterns, \( p_k \), and expansion coefficients, \( a_k \). With SVD we find values for the first pattern and time-series under the condition that the covariance with the response is maximized. A solution to this problem is found by taking the singular value decomposition of the cross covariance matrix, \( C \):

\[
C = s(t)z^T(t) \tag{42}
\]

The theory of singular value decomposition states that for every m x n matrix, in this case \( C \), there exists an m x n matrix \( \Sigma \), and there exists an m x m orthogonal matrix \( U \) and an n x n orthogonal matrix \( V \) such that (Lay, 1997):

\[
C = U \Sigma V^T \tag{43}
\]

The vectors in matrix \( U \) are the eigenvectors of \( C^T C \) and called the left singular vectors. As \( U \) is ns by ns it is natural to use the matrix \( U \) as an orthonormal basis for the data in \( S \). In this specific case the first row of matrix \( U \) contains values by which we can average the field data to one time-series or expansion coefficient.

\[
a(t) = \sum_{i=1}^{n_s} u_{1i} s_i(t) \tag{44}
\]

2.4.3 Pseudo operational testing

From an initial calibration period, which depended on the length of the time-series, models were tested over the period 1973 to 2004. The models were derived over a period till year t-1 and tested over year t. Also the PCA and SVD expansion coefficients of the sea surface temperature and geopotential height fields were calculated from data till year t-1. After testing the model, containing beta coefficients and if applied also expansion coefficients, were retrained and tested for the next year.

This procedure is analogous to the way in which new observations might be assimilated by an operational model. Another important reason to prefer this testing technique over for example Jack-knife testing was the stability of the predictors. The indices but especially the correlated sea surface temperature fields showed instable
behaviour (see Results chapter). With Jack-knife techniques, models are trained over all available years except for the test years and some years previous and after this test year. Models with temporal and spatial instable predictors such as sea surface temperatures may perform well if the test year is chosen in the middle of the evaluated period, but bad if the test year is chosen at the boundaries. Average model performance would in that case seem better than could ever be achieved in an operational situation.

There is however also a drawback of evaluating the model in the suggested ‘pseudo operational’ context compared to Jack-knife testing. Though we carefully removed trends from the responses, there still may be some long term trends. If predictions and response contain the same trend, the skill indicator correlation coefficient may be high though the skill of the forecast compared to climatology is low.

### 2.4.4 Forward selection

With forward selection we reduced the parameter sets resulting from correlation analysis. The most skilful predictor was selected first and secondly the predictor that adds most skill to the model was chosen. This process was repeated until an optimum was reached. An alternative to forward selection is backward elimination. Backward elimination starts with all parameters in the model and the ones with smallest coefficients are subsequently removed till an optimum is reached. Backward elimination has an advantage over forward selection, because it recognises sets of parameters that have considerable predictive capability even though any subset of them does not (Dallal, 2001). Because we used only limited number of parameters, or parameters derived with PCA and thus orthogonal, we expected no such predictive capability and applied forward selection.

### 2.4.5 Performance indicators

Model performance was measured with performance indicators. The first indicator is the correlation $r$ of the time-series of the forecasted response with the time-series of the measured response. As a second performance indicator we used the average of the bias errors. The bias error is the difference between the forecasted response $y_m$ and the measured response $y_o$. The mean bias error (MBE) should be close to zero.

$$MBE = \frac{\sum (y_o - y_m)}{n}$$ \hspace{1cm} (45)

The third measure of skill was the Root Mean Squared Error (RMSE). The RMSE is defined as the squared root of the average of the squared deviations of the model predictions $y_m$ from the observations $y_o$:

$$RMSE = \sqrt{\frac{\sum (y_o - y_m)^2}{n}}$$ \hspace{1cm} (46)
The RMSE can be compared to the standard deviation of the measured values; a model is only valuable if the RMSE is significantly smaller than this standard deviation. The last performance indicator was the true sign forecast. Forecasts are true sign forecast, if the model result and the measured values are both below (above) average. In model exercises like this when the explained variance of the model is low, most value should be given to the sign of the forecast and less to the magnitude. In other words model results may be useful as indicators if the water temperature or discharge will be below or above average, but a more precise forecast may not be expected.

2.4.6 Inflated regression

The predictors in this study have only a small correlation to the response. As a consequence the variance of the results of a multiple linear regression model, containing these predictors is small. The variance of regression forecast can be made equal to the variance of the response by using inflated regression equations (Colman, 1997). In an inflated regression equation the beta coefficient $\beta_i$ is divided by the correlation $r_i$ between the predictor and the response. If the model is used for testing purposes this correlation is calculated over the period until t-1.

$$y = \beta_0 + \frac{\beta_i}{r_i} x_i$$  

(47)
3 Results

3.1 Parameters

Water temperature, discharge, geopotential height and sunspot number data were cleaned with a moving average window based on Fourier analysis. The sea surface temperatures, North Atlantic Oscillation Index and Arctic Oscillation were anomalies, so no cleaning was necessary. As the largest trend was visible in the water temperature time-series, the window size and shape were chosen for the water temperature series. The chosen moving average was then applied to the other responses and predictors.

The first estimate for the size of the moving average window was determined with a Fourier analysis on the water temperature data. A uniform window of 20 years removed most of the long term trend in July and August water temperatures. As an example, Figure 26 compares the performance of a uniform 20 year window to the performance of a uniform 40 year window for August water temperatures. A similar result was found for windows with sines shape with a width of 30 years. This larger window width is however more sensitive to assumptions at the boundaries and therefore a uniform window was chosen.

Figure 26 suggests that there is a high frequency cyclic component with a return period of three years in the August water temperatures. The periods between the summers with cooling water problems 1976, 1994, 2003 and 2006 all equal multiples of three years, but this is too little evidence to confirm the speculation. In July water temperatures the first peak was wider, covering return periods of 2 and 3 years.

![Figure 26: return periods of cyclic components in the August water temperatures for two window sizes. The y-axis represents a measure for the size of the amplitude of the different cyclic components and equals the sum of the squared amplitudes. The long term trend is clearly visible for the uniform window with a width of 40 years, whereas this trend is for a large part removed for the smaller window of 20 years. For shorter return periods, the same cyclic components are found.](image)

The 20 year moving average filtered out most of the long term linear trend as can be viewed from Figure 27. No linear trend was left in the cleaned July water temperatures and the August trend was small: about 0.3 °C over the period from 1950 to 2004. Still the decadal variation is visible.
The basic statistics of the original and cleaned response series were analysed. The mean summer water temperature was higher in August than in July, where discharges are lower in July than in August. August monthly average water temperatures have eight times exceeded the critical threshold of 23 °C in over the period from 1950 to 2004. The standard deviation of summer water temperature can be considered small. The standard deviations of the cleaned series are logically smaller than the original series and their mean is close to zero. The standard deviations can be used as a measure to compare model results.

Table 8: basic statistics of the original and the responses, where a moving average of twenty years was removed, over the period 1950 to 2004.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>WT7 original</th>
<th>WT7 cleaned</th>
<th>WT8 original</th>
<th>WT8 cleaned</th>
<th>Q7 original</th>
<th>Q7 cleaned</th>
<th>Q8 original</th>
<th>Q8 cleaned</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>20.65</td>
<td>0.00</td>
<td>20.95</td>
<td>-0.02</td>
<td>2156</td>
<td>7</td>
<td>1807</td>
<td>10</td>
</tr>
<tr>
<td>standard deviation</td>
<td>1.67</td>
<td>1.45</td>
<td>1.53</td>
<td>0.96</td>
<td>630</td>
<td>629</td>
<td>477</td>
<td>462</td>
</tr>
<tr>
<td>above 23 °C</td>
<td>5</td>
<td>-</td>
<td>8</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>above 24 °C</td>
<td>1</td>
<td>-</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>below 1500 m³/s</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>6</td>
<td>-</td>
<td>16</td>
<td>-</td>
</tr>
<tr>
<td>below 1100 m³/s</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2</td>
<td>-</td>
<td>6</td>
<td>-</td>
</tr>
</tbody>
</table>

3.2 Linear correlation analysis

3.2.1 Indices
The North Atlantic Oscillation Index and Arctic Oscillation index were both positively correlated with summer water temperatures and negatively with discharge. Correlations were significant, but coefficients were small with maximum absolute values around 0.3. The positive correlation between summer water temperatures and NAO or AO index may physically be explained by the strong correlation between (N)AO and the sea surface temperature pattern of which an example is given in Figure 28. A combination of advective transport and warming of winds may lead to warmer summers if the ocean water temperature is above average.

The latter correlation may be physically consistent as precipitation quantities in Southern and Middle Europe are generally below average during phases of positive...
(N)AO. If summer discharge consists for an important part of melting water, preceding winter snowfall in the Alps may be an important summer discharge indicator. Moreover are evaporation rates higher when air temperatures are high, which is again associated with a positive winter (N)AO. However an important part of the discharge in the low flow season origins from groundwater. If there would be any correlation between winter (N)AO and the groundwater recharge, we would expect a positive correlation, because a positive (N)AO index is associated with strong westerlies and more precipitation in northern Europe.

Table 9; correlations of winter atmospheric indices and sunspots with summer water temperature WT and discharges Q in the months July 7 and August 8 over the period from 1950-2004.

<table>
<thead>
<tr>
<th>Index</th>
<th>Month</th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAO</td>
<td>January</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>February</td>
<td>-</td>
<td>0.31*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>March</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>AO</td>
<td>January</td>
<td>-</td>
<td>-</td>
<td>-0.28*</td>
<td>-0.28*</td>
</tr>
<tr>
<td></td>
<td>February</td>
<td>-</td>
<td>0.33*</td>
<td>-</td>
<td>-0.32*</td>
</tr>
<tr>
<td></td>
<td>March</td>
<td>0.33*</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>SUN</td>
<td>January</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>February</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>March</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

*significant at p=0.05 level **significant at p=0.01 level

Figure 28; correlation map February North Atlantic Oscillation Index and Sea Surface Temperatures (ICOADS data set). The correlation pattern suggests that during positive phases of the NAO the Gulf stream water temperatures are higher, which may cause higher summer water temperatures in the Netherlands.

Johansson (1998) suggested that interdecadal climate variations may be more important to Europe than annual variations, when compared to the United States. Therefore the correlation of the significantly correlated parameters with lag times up to four years was evaluated. Indeed some skill was found for years previous to the response (see Table 10). The August water temperature predictor NAO2 had significant correlations up to two years previous to the response. Because these time-series were strongly auto-correlated, the expansion coefficient of the first principle component over the first two lag times was calculated:
\[ PCNAO2\text{lag0}1 = \begin{bmatrix} NAO2\text{lag0} & NAO2\text{lag1} \\ 0.70 & 0.71 \end{bmatrix} \] (48)

The correlation of the first principle component of the NAO for these two years was higher than the correlation of any individual NAO. August discharge and AO1 were significantly correlated for lag times of zero and two years. The expansion coefficient of the principle component of series with lags from zero to two years was calculated:

\[ PCAO1\text{lag0}12 = \begin{bmatrix} AO1\text{lag0} & AO1\text{lag1} & AO1\text{lag2} \\ 0.55 & 0.61 & 0.57 \end{bmatrix} \] (49)

Also this first principle component of AO1 showed higher correlations to the response August water temperatures than any of the individual predictors.

Table 10: Correlation of atmospheric indices for lag times up to 4 years and correlations of principle components of the indices with lag times. Differences between this table and previous correlation table are due to the shorter evaluated time period from 1954 to 2004.

<table>
<thead>
<tr>
<th>Lag</th>
<th>WT7 AO3</th>
<th>WT8 NAO2</th>
<th>Q7 AO2</th>
<th>Q8 AO1</th>
<th>Q8 AO2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 years</td>
<td>0.37**</td>
<td>0.32*</td>
<td>0.33*</td>
<td>-0.27*</td>
<td>-0.27*</td>
</tr>
<tr>
<td>1 year</td>
<td>-</td>
<td>0.36**</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2 years</td>
<td>-</td>
<td>0.26*</td>
<td>-</td>
<td>-</td>
<td>-0.28*</td>
</tr>
<tr>
<td>3 years</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>4 years</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PCNAO2\text{lag01}</td>
<td>0.42**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PCAO1\text{lag012}</td>
<td>-0.40**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*significant at \( p=0.05 \) level. **significant at \( p=0.01 \) level.

The correlations of the indices over the period from 1950 to 2004 were significant, but temporal instabilities were found. Figure 13 shows two examples of how the correlation between responses and AO predictors was instable, when the period was divided in two parts. The correlation between the Arctic Oscillation index in March and July water temperatures has been stronger in the last decades than it was over the period from 1955 to 1979. The correlation between AO in February and discharge in August showed an opposite behaviour. The high significant correlation of the first half of the period is reduced to an insignificant correlation in the second half.
Figure 29; Two examples of instable predictors response relationships. The left picture shows the relationship between July water temperatures and March Artic Oscillation index and the right picture the relationship between Arctic Oscillation Index in February and August discharge. The closed squares are the period 1950 to 1977 and the open squared the period from 1978 to 2004.

The results of the stability analysis are summarised in Table 3. Most predictors showed some instable behaviour. The most stable predictor was the expansion coefficient of the principle component of the January AO with lag times up to two years, PCAO1lag012. The magnitude of the found instabilities was however strongly dependent on the choice of the two time periods and on the cleaning of data with a moving average window.

Table 11; Stability of correlation between responses and atmospheric indices. Correlations over the period 1950 to 2004 were compared to the correlations in two parts of this periods. Correlations were stable if values did not vary much.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>WT7</td>
<td>AO3</td>
<td>0.37*</td>
<td>0.25*</td>
<td>0.44**</td>
</tr>
<tr>
<td>WT8</td>
<td>AO2</td>
<td>0.33*</td>
<td>0.38**</td>
<td>0.28*</td>
</tr>
<tr>
<td></td>
<td>NAO2</td>
<td>0.32*</td>
<td>0.26*</td>
<td>0.40**</td>
</tr>
<tr>
<td></td>
<td>PCNAO2lag01</td>
<td>0.42**</td>
<td>0.35*</td>
<td>0.55**</td>
</tr>
<tr>
<td>Q7</td>
<td>AO1</td>
<td>-0.30*</td>
<td>-0.27*</td>
<td>-0.37*</td>
</tr>
<tr>
<td>Q8</td>
<td>AO1</td>
<td>-0.27*</td>
<td>-0.36**</td>
<td>-0.16</td>
</tr>
<tr>
<td></td>
<td>AO2</td>
<td>-0.35**</td>
<td>-0.56*</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>PCAO11lag012</td>
<td>-0.40**</td>
<td>-0.40**</td>
<td>-0.46**</td>
</tr>
</tbody>
</table>

*significant at p=0.05 level. **significant at p=0.01 level.

3.2.2 Sea surface temperature

The strongest correlations for all responses were found for time-series at grid points in the sea surface temperature field. Maximum absolute values ranged from 0.5 for July discharge and August water temperature to 0.4 for July water temperature. March sea water temperatures seems to have highest skill in forecasting July water temperatures, as the number of significantly correlated time-series as well as the maximum found correlation is highest for this field. The highest correlation for August water temperatures was also found in the March sea surface temperature field, but the number of correlated time-series was higher in February. July discharges were strongest correlated with January water temperatures. The largest number of correlated predictors for August discharge was found for March sea surface temperatures, but the average correlation was highest in January.
Table 12: Descriptive statistics of the correlations in the Sea surface temperature fields over the period 1950-2004.
The number of significantly correlated time-series in the global field of 36 x 72 grid points are given and the maximum and average correlation over this set.

<table>
<thead>
<tr>
<th></th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>SST1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>time-series p=0.05</td>
<td>64</td>
<td>60</td>
<td>112</td>
<td>72</td>
</tr>
<tr>
<td>maximum r</td>
<td>0.36*</td>
<td>0.36*</td>
<td>0.50**</td>
<td>0.45**</td>
</tr>
<tr>
<td>average r</td>
<td>0.30*</td>
<td>0.29*</td>
<td>0.31*</td>
<td>0.33*</td>
</tr>
<tr>
<td>SST2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>time-series p=0.05</td>
<td>64</td>
<td>97</td>
<td>78</td>
<td>85</td>
</tr>
<tr>
<td>maximum r</td>
<td>0.37*</td>
<td>0.42**</td>
<td>0.43**</td>
<td>0.42**</td>
</tr>
<tr>
<td>average r</td>
<td>0.30*</td>
<td>0.31</td>
<td>0.31</td>
<td>0.32</td>
</tr>
<tr>
<td>SST3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>time-series p=0.05</td>
<td>85</td>
<td>75</td>
<td>92</td>
<td>129</td>
</tr>
<tr>
<td>maximum r</td>
<td>0.41**</td>
<td>0.50**</td>
<td>0.42**</td>
<td>0.45**</td>
</tr>
<tr>
<td>average r</td>
<td>0.30*</td>
<td>0.34*</td>
<td>0.32*</td>
<td>0.31*</td>
</tr>
</tbody>
</table>

* significant at p=0.05 level. ** significant at p=0.01 level.

The geographical location of the correlating sea surface temperature areas was rather stable over the three evaluated winter months. The July water temperatures are positively correlated with sea surface temperatures in the Baltic Sea and the Atlantic Ocean south of West Africa, whereas negative centres are found south east of Greenland and in the Atlantic Ocean between the equator and the tropic of Cancer (Figure 11). The correlation map for August in Figure 12 lacks this last negative centre, but has larger positive centres over the Atlantic and even the Indian and Pacific Ocean. The correlation between summer discharges and sea surface temperatures in the Baltic Sea and the Atlantic Ocean south of West Africa is of the opposite, negative, sign. Figure 13 shows how these two negative centres form a tri-pole pattern together with a negative correlation centre in front of the United States west coast.

![Figure 30: Correlations WT7 and SST1](image)

Figure 30: Correlations (significance level p=0.05) between July water temperatures and January sea surface temperatures (Kaplan Extended SST V2). The x indicate grid points where correlations were significant at the 0.01 level. Similar maps were found for correlations between July water temperatures and February and March sea surface temperatures.
Figure 31: correlations (significance level $p=0.05$) between August water temperatures and January sea surface temperatures (Kaplan Extended SST V2). The x indicate grid points where correlations were significant at the 0.01 level. Similar maps were found for correlations between August water temperatures and February and March sea surface temperatures.

Figure 32: correlations (significance level $p=0.05$) between July discharges and February sea surface temperatures (Kaplan Extended SST V2). The x indicate grid points where correlations were significant at the 0.01 level. Similar maps were found for correlations between July discharges and January and March sea surface temperatures as well as for August discharges.
The correlations between the significantly correlated time-series were calculated and values for some points approached zero, indicating that the time-series were independent. The skill of the field with independent correlating time-series was evaluated with the principle components of the correlating time-series in the winter sea surface temperature fields. For each correlated sea surface temperature field the five most explaining principle components were calculated. The left picture in Figure 18 shows the results for March sea surface temperatures and water temperatures in July. The first principle component explained most of the field variance in the correlated sea surface temperature field and had highest correlation to July water temperatures. Both the explained field variance as the correlation to the response decreased for higher order principle components. This was however not necessarily the case as can be viewed from the right picture in Figure 18, where the fourth principle component has highest correlation to the response.
Figure 34; examples of principle component analysis of correlated time-series at grid points in the Sea surface temperature fields. The left picture shows the EOFs or principle components of the March Sea Surface temperature field that was correlated to July water temperatures. The right picture shows the principle components of the January sea surface temperature field that was correlated to August water temperatures.

By calculating the multiple correlations of the first five principle components, we could approximate the maximum explained correlation of each field. Like the results in the previous table indicated March sea surface temperature was the best predictor for July water temperatures, whereas for the other responses January sea surface temperatures scored highest.

Table 13; Maximum field correlations approximated with principle components (1950-2004).

<table>
<thead>
<tr>
<th>Field</th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>SST1</td>
<td>0.59</td>
<td>0.52</td>
<td>0.69</td>
<td>0.68</td>
</tr>
<tr>
<td>SST2</td>
<td>0.54</td>
<td>0.51</td>
<td>0.54</td>
<td>0.60</td>
</tr>
<tr>
<td>SST3</td>
<td>0.64</td>
<td>0.48</td>
<td>0.68</td>
<td>0.65</td>
</tr>
</tbody>
</table>

The skill of sea surface temperature predictors was however smaller due to unstable behaviour. The stability of the first selection of significantly correlated parameters from which the principle components were derived was evaluated. The correlation patterns in the sea surface temperature appeared to be very unstable. The location of the significantly correlated time-series changed for subsets as is illustrated with two examples in Figure 35 and Figure 36. These figures shows how the significantly correlated grid points over the whole data set were different from most of the significantly correlated grid points in both the first and the second halve of the dataset.
Figure 35; instability of correlations Q7 and SST1 at p=0.05. The coloured areas are the significant correlations over the period 1950 to 2004. The squares indicate significant correlations over the period 1950 to 1978 and the rounds over the period 1979 to 2004.

Figure 36; instability of correlations WT8 and SST3 at p=0.05. The coloured areas are the significant correlations over the period 1950 to 2004. The squares indicate significant correlations over the period 1950 to 1978 and the rounds over the period 1979 to 2004.
3.2.3 Pressure fields

The results of the correlation analysis for geopotential height fields are presented in Table 14. Geopotential heights were especially strongly correlated with August water temperatures with absolute values up to 0.5. The August responses were strongest correlated with the January geopotential height field, whereas July water temperatures were strongest correlated with March fields and July discharges with fields in February.

Table 14; descriptive statistics of the correlations in the geopotential height fields over the period 1950-2004. The number of significantly correlated time-series in the northern hemisphere field of 18 x 36 grid points are given and the maximum and average correlation over this set.

<table>
<thead>
<tr>
<th></th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z5001</td>
<td>time-series p=0.05</td>
<td>37</td>
<td>47</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>maximum correlation</td>
<td>0.41**</td>
<td>0.54**</td>
<td>0.37**</td>
</tr>
<tr>
<td></td>
<td>average correlation</td>
<td>0.33*</td>
<td>0.37*</td>
<td>0.31*</td>
</tr>
<tr>
<td>Z5002</td>
<td>time-series p=0.05</td>
<td>46</td>
<td>73</td>
<td>41</td>
</tr>
<tr>
<td></td>
<td>maximum correlation</td>
<td>0.44**</td>
<td>0.42**</td>
<td>0.37**</td>
</tr>
<tr>
<td></td>
<td>average correlation</td>
<td>0.32*</td>
<td>0.33*</td>
<td>0.30*</td>
</tr>
<tr>
<td>Z5003</td>
<td>time-series p=0.05</td>
<td>61</td>
<td>19</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>maximum correlation</td>
<td>0.38**</td>
<td>0.35*</td>
<td>0.39**</td>
</tr>
<tr>
<td></td>
<td>average correlation</td>
<td>0.32*</td>
<td>0.30*</td>
<td>0.31*</td>
</tr>
</tbody>
</table>

*significant at p=0.05 level. **significant at p=0.01 level.

NAO is a principle component of normalized sea level pressure and even though we used 500 mPa geopotential heights as predictor, correlation patterns similar to NAO were expected. Indeed for water temperatures positive correlations were found above the Azores and negative correlations above Iceland. Figure 37 gives an example of the correlation pattern for August water temperatures and February geopotential heights. The pattern in this figure shows large similarities to the correlation map for February NAO and geopotential heights in Figure 38.

![Figure 37; correlations (significance level p=0.05) between August water temperature and February geopotential heights.](image-url)
Correlations NAO2 and Z5002

Figure 38: correlations (significance level p=0.05) between the North Atlantic Oscillation index in February and February geopotential heights.

Also in the correlation maps for discharge a NAO pattern was recognizable. Discharges were negatively correlated with the geopotential heights above the Azores and positive with the geopotential heights above Iceland. An example for July water temperatures and January geopotential heights is given in Figure 39.

Correlations Q7 and Z5001

Figure 39: correlations (significance level p=0.05) between July discharge and February geopotential heights.

Analogue to the procedure followed for sea water temperatures the multiple correlations of the first five principle components were calculated. The values in Table 15 confirm the conclusions drawn upon the results Table 14: July water temperatures were strongest correlated with March geopotential heights, July discharges with February geopotential heights and both August responses with January geopotential heights.

Table 15: maximum fields correlations approximated with principle components.

<table>
<thead>
<tr>
<th>Field</th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z5001</td>
<td>0.48**</td>
<td>0.62**</td>
<td>0.46**</td>
<td>0.48**</td>
</tr>
<tr>
<td>Z5002</td>
<td>0.48**</td>
<td>0.57**</td>
<td>0.53**</td>
<td>0.48**</td>
</tr>
<tr>
<td>Z5003</td>
<td>0.57**</td>
<td>0.53**</td>
<td>0.45**</td>
<td>0.48**</td>
</tr>
</tbody>
</table>

*significant at p=0.05 level. **significant at p=0.01 level.

Like for sea surface temperature we found large instabilities in the correlation patterns for the split sample. An example of the instabilities in the relationship between August water temperatures and January geopotential height fields is given in Figure 40.
### 3.3 Multiple correlation

The previous paragraphs analyzed the correlations of the responses to single time-series and the multiple correlations of fields. A logical next question is whether a combination of the different parameter groups would increase correlation coefficients and thereby skill. We considered three groups of parameters, which were largely dependent. The North Atlantic and Arctic Oscillation index describe patterns derived from pressure fields that are also visible in the sea surface temperature field. The correlation between NAO and AO ranges from 0.7 to 0.8 over the evaluated months. Because of these interdependencies, a large increase of correlation for more groups, when compared to one group of parameters was not expected.

We calculated the multiple correlations of the significantly correlated indices and sea surface temperature fields. The information of the correlated sea surface temperature fields of the three months was reduced to five principle components. The significantly correlated principle components were used in the multiple correlation analysis next to the significantly correlated predictors. The multiple correlation coefficients were close to the correlation coefficients found for the sea surface temperature fields in Table 13. The small differences were partly caused by the difference in evaluated time period. We may conclude that the skill of combinations of fields and indices is not significantly larger that the skill of the field itself.

Table 16: combined correlation of predictors estimated with a multiple linear regression equation over the period 1955-2004. The table shows the results of combination of sea surface temperatures and indices.

<table>
<thead>
<tr>
<th>Response</th>
<th>Predictors</th>
<th>( r_{total} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>WT7</td>
<td>AO3, SSTPC1, SSTPC2, SSTPC3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( r )</td>
<td>0.37**, 0.50**, -0.38**, -0.32*</td>
</tr>
<tr>
<td></td>
<td>beta</td>
<td>0.19, 0.34, -0.49, -0.55</td>
</tr>
<tr>
<td>WT8</td>
<td>AO2, NAO2, PCNAO2lag01, SSTPC1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( r )</td>
<td>0.33*, 0.32*, 0.42**, 0.48**</td>
</tr>
<tr>
<td></td>
<td>beta</td>
<td>0.16, -0.28, 0.28, 0.05</td>
</tr>
<tr>
<td>Q7</td>
<td>AO1, SSTPC1, SSTPC2, SSTPC3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( r )</td>
<td>-0.27*, -0.55**, 0.27*, 0.51**</td>
</tr>
<tr>
<td></td>
<td>beta</td>
<td>-11, -112, 105, 255</td>
</tr>
<tr>
<td>Q8</td>
<td>AO1, AO2, PCAO1lag012, SSTPC1, SSTPC3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( r )</td>
<td>-0.27*, -0.35*, -0.40**, -0.61**, 0.45**</td>
</tr>
<tr>
<td></td>
<td>beta</td>
<td>-16, -26, -48, -60, 162</td>
</tr>
</tbody>
</table>

*significant at \( p=0.05 \) level. **significant at \( p=0.01 \) level.
3.4 Forecast models

3.4.1 Indices

The first series of models was derived with indices as predictors. All indices and principle components that were significantly correlated (previous paragraph) were tested alone and in combinations. Forward selection resulted in the multiple linear regression equations (50) to (53). The correlation analysis found only one significantly correlated predictor for July water temperatures and discharge, respectively AO3 and AO1, so the regression equations for these responses contain only one predictor. For August water temperature and discharge more predictors were found, but these were highly dependent. Therefore the best ‘indices models’ for these responses only contain one most skilful predictor as well.

\[
\begin{align*}
WT7 &= \beta_0 + \beta_1 AO3 \\
WT8 &= \beta_0 + \beta_1 EOFNAO2lag01 \\
Q7 &= \beta_0 + \beta_1 AO1 \\
Q8 &= \beta_0 + \beta_1 EOPAO1lag012 
\end{align*}
\]

Table 11 presents the performance indicators of the four models over the test period from 1972 to 2004. The August water temperature and August discharge model performed best. The skill of the July discharge model was smaller and the correlation coefficient of the July water temperature model even insignificant. These skill differences could be explained with the correlation coefficients and significances that were found in the previous chapter. Correlation coefficients of the predictors in the August models were higher than the correlation coefficients of the predictors in the July model. PCFAO1lag012 was the most stable predictor and this model performed indeed best.

The forecasts had a smaller variance than the measured data, due to the moderate correlation between the trainings data. In Figure 41 to Figure 44 the variance of the forecast data was made approximately equal to the variance of the observations by using inflated forecast. The correlation coefficients of the inflated forecasts and of the inflated forecasts with trends are given in Table 17 as \( r_{\text{inflated}} \) and \( r_{\text{trend}} \). The values with added trend are logically larger than the values for the cleaned series, but the values of the cleaned series are more correct skill measures.
If we focus on the three summers with severe cooling water problems we see that the July water temperature model captured the correct sign, but the August water temperature model did not. The 1994 and 2003 droughts were captured. The August water temperature model showed however a strong positive bias over the last decade of the test period, which makes results less valuable.

Figure 41; example of results of the index models for July water temperatures. The graph shows the inflated model results, which means that the beta coefficient in the regression equation was divided by the correlation between the predictor and response.

Figure 42; example of results of the index models for July discharge. The graph shows the inflated model results, which means that the beta coefficient in the regression equation was divided by the correlation between the predictor and response.
3.4.2 Sea surface temperature fields

We limited the sea surface temperature field to an ‘extended Atlantic Ocean’ from 40 degrees south to 90 degrees north and 100 degrees west to 70 degrees east. In this way we included most significantly correlated centres. The presented PCA and SVD models appeared to be sensitive to this geographical limitation: results were better for this limited field than for a global field.

Similar to the correlation analysis we calculated the first five principle components of the sea surface temperature field till t-1. The principle components that were significantly correlated to the response were selected as parameters in the multiple regression equation to a maximum of three. The results of the PCA models are depicted in Table 18. The by far best performance was found for August water temperature with the sea surface temperature field in February as predictor. We could ask why this August water temperature model performs better than the other models. The absolute correlation values in the correlation analysis were for all responses in a
similar range. Therefore we may expect that the bad performance of the other three models was mainly caused by larger instabilities in the correlated sea surface temperature field.

Table 18: Results of PC models with SST fields as predictors. The model was tested over the period 1972 to 2004 and trained from 1933 to the year previous to the test year.

<table>
<thead>
<tr>
<th>Predictor field</th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>SST1 r</td>
<td>0.19</td>
<td>0.22</td>
<td>0.00</td>
<td>0.03</td>
</tr>
<tr>
<td>true sign</td>
<td>0.58</td>
<td>0.61</td>
<td>0.58</td>
<td>0.58</td>
</tr>
<tr>
<td>MBE</td>
<td>-0.32</td>
<td>0.12</td>
<td>-118</td>
<td>-59</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.65</td>
<td>0.92</td>
<td>677</td>
<td>442</td>
</tr>
<tr>
<td>SST2 r</td>
<td>0.11</td>
<td>0.52**</td>
<td>0.14</td>
<td>0.30*</td>
</tr>
<tr>
<td>true sign</td>
<td>0.48</td>
<td>0.70</td>
<td>0.64</td>
<td>0.52</td>
</tr>
<tr>
<td>MBE</td>
<td>0.21</td>
<td>0.25</td>
<td>-105</td>
<td>-81</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.66</td>
<td>0.83</td>
<td>643</td>
<td>405</td>
</tr>
<tr>
<td>SST3 r</td>
<td>-0.09</td>
<td>0.17</td>
<td>0.05</td>
<td>0.25</td>
</tr>
<tr>
<td>true sign</td>
<td>0.42</td>
<td>0.58</td>
<td>0.55</td>
<td>0.55</td>
</tr>
<tr>
<td>MBE</td>
<td>0.17</td>
<td>0.16</td>
<td>-63</td>
<td>-32</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.73</td>
<td>0.99</td>
<td>678</td>
<td>435</td>
</tr>
<tr>
<td>SSTall r</td>
<td>0.10</td>
<td>0.32*</td>
<td>0.14</td>
<td>0.18</td>
</tr>
<tr>
<td>true sign</td>
<td>0.39</td>
<td>0.67</td>
<td>0.64</td>
<td>0.70</td>
</tr>
<tr>
<td>MBE</td>
<td>0.30</td>
<td>0.25</td>
<td>-125</td>
<td>-88</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.69</td>
<td>0.92</td>
<td>653</td>
<td>427</td>
</tr>
</tbody>
</table>

* significant at the p=0.05 level ** significant at the p=0.01 level.

The results of the August water temperature model over the test period from 1973 to 2004 are presented in Figure 45. Again the correlation of the time-series in this graph was much larger than the correlation of the cleaned time-series. The variance of the forecasts was smaller than the variance of the response. Analogue to the procedure followed with the index models, we tried to inflate the forecast with the correlation coefficients between predictor and response. This however led to instable model results that can be viewed in Figure 46. A reason for this instability could be that the forecasts were based on a multiple linear regression equation rather than a single parameter linear regression equation. More important was probably that the principle components were recalculated after each test year and therefore their magnitude number and correlation varied.

Figure 45; results of the principle component SST model for August water temperatures. The correlation for the series with trend is 0.8.
Figure 46: results of inflated principal component SST model for August water temperatures. The graph shows the inflated model results, which means that the beta coefficient in the regression equation was divided by the correlation between the predictor and response.

The overall performance of the SVD models was less. Table 19 showed that again performance was best for the August water temperature model, smaller for August discharges and insignificant for the July responses.

Table 19: Results of SVD models with SST fields as predictors. The model was tested over the period 1972 to 2004 and trained from 1933 to the year previous to the test year.

<table>
<thead>
<tr>
<th>Predictor field</th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>SST1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>0.06</td>
<td>0.16</td>
<td>0.08</td>
<td>0.21</td>
</tr>
<tr>
<td>true sign</td>
<td>0.55</td>
<td>0.61</td>
<td>0.52</td>
<td>0.61</td>
</tr>
<tr>
<td>MBE</td>
<td>0.19</td>
<td>0.20</td>
<td>-50</td>
<td>-67</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.64</td>
<td>0.98</td>
<td>667</td>
<td>424</td>
</tr>
<tr>
<td>SST2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>0.09</td>
<td>0.42</td>
<td>0.06</td>
<td>0.22</td>
</tr>
<tr>
<td>true sign</td>
<td>0.61</td>
<td>0.67</td>
<td>0.48</td>
<td>0.61</td>
</tr>
<tr>
<td>MBE</td>
<td>0.21</td>
<td>0.21</td>
<td>-55</td>
<td>-78</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.59</td>
<td>0.87</td>
<td>655</td>
<td>421</td>
</tr>
<tr>
<td>SST3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>0.14</td>
<td>0.43</td>
<td>0.14</td>
<td>0.32</td>
</tr>
<tr>
<td>true sign</td>
<td>0.58</td>
<td>0.55</td>
<td>0.52</td>
<td>0.58</td>
</tr>
<tr>
<td>MBE</td>
<td>0.32</td>
<td>0.22</td>
<td>-62</td>
<td>-60</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.61</td>
<td>0.87</td>
<td>661</td>
<td>414</td>
</tr>
<tr>
<td>SSTall</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>0.09</td>
<td>0.33</td>
<td>0.11</td>
<td>0.33</td>
</tr>
<tr>
<td>true sign</td>
<td>0.58</td>
<td>0.64</td>
<td>0.58</td>
<td>0.61</td>
</tr>
<tr>
<td>MBE</td>
<td>0.28</td>
<td>0.26</td>
<td>-65</td>
<td>-80</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.66</td>
<td>0.93</td>
<td>674</td>
<td>423</td>
</tr>
</tbody>
</table>

3.4.3 Geopotential heights

The principle component model was also tested with geopotential heights as predictor. The performance for July water temperatures was slightly better than the performance of the sea surface temperature principle component model. No better results were obtained for the other responses. Instabilities and missing values were the reasons that the correlation values in the correlation analysis are not reached in the forecast model. The SVD model gave no valuable results.
3.4.4 Combination

We tried to combine the skill of sea surface temperatures and indices in one model. The best performing field models were combined with the best performing index models. Performance was however less than the performance of the individual models. The performance difference with the sea surface temperature models was caused by the difference in train time. This train time was 40 years for the sea surface temperature models, but only 19 years for the combined models, because the length of the indices’ time-series was shorter. However, even if both models were trained over the same time period, no large performance increase was expected for the combination model. The correlation analysis already showed that the multiple correlations of sea surface temperatures and indices with the responses were close to the correlations of only sea surface temperatures with the responses.

Table 20; Results of PC models with Z500 fields as predictors. The model was tested over the period 1972 to 2004 and trained from 1933 to the year previous to the test year.

<table>
<thead>
<tr>
<th></th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z5001 R</td>
<td>0.19</td>
<td>0.36</td>
<td>0.00</td>
<td>0.31</td>
</tr>
<tr>
<td>true sign</td>
<td>0.42</td>
<td>0.45</td>
<td>0.48</td>
<td>0.52</td>
</tr>
<tr>
<td>MBE</td>
<td>-0.12</td>
<td>-0.10</td>
<td>57</td>
<td>34</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.78</td>
<td>0.94</td>
<td>753</td>
<td>417</td>
</tr>
<tr>
<td>Z5002 R</td>
<td>0.20</td>
<td>0.07</td>
<td>0.00</td>
<td>0.07</td>
</tr>
<tr>
<td>true sign</td>
<td>0.36</td>
<td>0.48</td>
<td>0.18</td>
<td>0.42</td>
</tr>
<tr>
<td>MBE</td>
<td>-0.34</td>
<td>0.05</td>
<td>20</td>
<td>-15</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.73</td>
<td>1.00</td>
<td>758</td>
<td>449</td>
</tr>
<tr>
<td>Z5003 R</td>
<td>0.16</td>
<td>0.00</td>
<td>-</td>
<td>-0.10</td>
</tr>
<tr>
<td>true sign</td>
<td>0.42</td>
<td>0.42</td>
<td>-</td>
<td>0.45</td>
</tr>
<tr>
<td>MBE</td>
<td>-0.04</td>
<td>0.08</td>
<td>-</td>
<td>-11</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.72</td>
<td>1.05</td>
<td>-</td>
<td>430</td>
</tr>
</tbody>
</table>

Table 21; Results of the combined EOF and indices models with SST fields as predictors. The model was tested over the period 1972 to 2004 and trained from 1955 to the year previous to the test year.

<table>
<thead>
<tr>
<th></th>
<th>WT7</th>
<th>WT8</th>
<th>Q7</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>predictor index</td>
<td>AO1</td>
<td>PCNAO2lag01</td>
<td>AO1</td>
<td>PCAO1lag012</td>
</tr>
<tr>
<td>predictor field</td>
<td>SST1</td>
<td>SST2</td>
<td>SST2</td>
<td>SST3</td>
</tr>
<tr>
<td>r</td>
<td>0.29</td>
<td>0.36</td>
<td>0.11</td>
<td>0.25</td>
</tr>
<tr>
<td>true sign</td>
<td>0.61</td>
<td>0.70</td>
<td>0.70</td>
<td>0.67</td>
</tr>
<tr>
<td>MBE</td>
<td>0.36</td>
<td>0.19</td>
<td>-172</td>
<td>22</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.59</td>
<td>0.93</td>
<td>682</td>
<td>432</td>
</tr>
</tbody>
</table>
4 Discussion

The maximum levels of correlation achieved with the models reached from 0.5 for August water temperatures and discharges to 0.4 for July water temperatures and 0.2 for July discharges. According to the correlation analysis the maximum correlation values were higher; between 0.5 and 0.7. This difference was caused by instabilities in the predictor response relationships, which especially showed for July responses. Statistically the worse performance in July may be caused by more instable predictor response relationships. Physically July discharge may, for example, be more influenced by shorter time scale phenomena, such as rainfall or the origin of this discharge is more subjected to fluctuations. The performance difference between models for July and August water temperatures was also found for air temperatures in similar studies by Colman (1999) or Wilby (2006).

![Correlation air and water temperature in July](image)

Figure 47; correlation monthly average July water temperature to air temperature (data source KNMI), over the period from 1909 to 2004

We may compare the results of this research with similar studies in Table 22. There were no studies found on seasonal forecast of water temperature, but water temperatures are strongly correlated with air temperature when evaluated on a monthly average basis (see Figure 47). Wilby and Colman used large scale oceanic atmospheric patterns as predictor to forecast summer hydrometeorology. Their and our statistical models outperform the physical model forecasts issued by ECMWF. The results of the August water temperature forecast are comparable with the results of research concerning statistical air temperature forecast in North-western Europe. The results obtained for July water temperatures are a bit lower.
The principle component of the NAO and AO with longer lag times was a good predictor. With pattern recognition techniques was tried to create a flexible model system to anticipate to the instable correlation patterns. These models using principle components however only outperformed the indices model for August water temperatures. The SVD model performed less for all responses. The PCA and SVD model were very sensitive to the chosen geographical extension and the PCA model to the set significance limit as well. Better results may be obtained by optimizing those parameters.

We estimated a maximum correlation, which was not achieved by the forecast models, mainly due to instabilities in the predictors. Regarding this stability we can make some critical remarks to the forecast methodology suggested by Colman (1997). Colman (1997) used a principal component of sea water temperatures TSE1, which showed resemblance to the correlation pattern. This principal component was derived over the period 1901 to 1990 and the correlation was tested in the publication till from 1871 till 1995. As we found that the correlation pattern was very instable, the skill of the principle components may also be instable. Colman (1997) noted that the correlation between the TSE 1 and Central England temperature (CET) over his 1871 to 1970 training period was small, 0.26, whereas the correlation over the testing period from 1971 to 1995 was 0.55. If the model has shown instable behaviour over these two periods, would it be stable in the future?

Model skill may be reduced if global climate change will cause changes in large scale patterns. For example the found correlation patterns can partly be explained, because the Dutch climate conditions are currently dominated by western currents. An increased dominance of south western currents has been observed over the last decades. KNMI (2006) predicts more eastern winds in summer, which may reduce the influence of Atlantic Ocean temperatures for our summer climate and therefore also negatively influence skill of the proposed method.
5 Conclusions and recommendations

5.1 Conclusions
Using multiple linear regression and pattern recognition techniques Principle Component analysis and Singular Value decomposition, models for seasonal forecast of Rhine summer discharge and water temperature were derived. Possible predictors were the North Atlantic Oscillation Index, the Arctic Oscillation Index, the sunspot number, the global sea surface temperature field and the northern hemisphere 500 hPa geopotential height in the months January, February and March.

The sunspot number was not significantly correlated to any of the responses. The Artic Oscillation Index and the North Atlantic Oscillation Index had small but significant correlation coefficients around 0.3. The skill of the AO and NAO were increased by taking the influence of predictors with longer lag times into account using principle component analysis. The correlation coefficients of respectively NAO and AO to August water temperatures and discharge was increased by taking the principal component of the predictor up to two or three years previous to the response.

The correlation analysis further showed that the sea surface temperature field and geopotential height field were significantly correlated with values up to 0.6, but that the correlation patterns were instable.

The linear regression models containing indices showed best overall performance. The correlations between the forecast and the response over the test period were 0.4 for July water temperatures, 0.5 for August water temperatures, 0.2 for July discharges and 0.5 for August discharges. The principle component model with sea surface temperatures as predictors only outperformed the index model for August water temperatures, but the difference was small. Results of this model for other responses and for the predictor geopotential height were less. The correlation coefficients of the models with time-series as results of singular value decomposition as predictors were smaller than the correlation coefficients of the index models. Combinations of the principle component model with the index model did not lead to improvement of the results.

Because of the low level of explained variance, possibilities of the suggested models for operational purposes are limited.

5.2 Recommendations
Further research could be done on the application of statistical models forecasting summer hydrometeorology to large scale oceanic atmospheric patterns. We recommend:

- Search for predictors with lag time from the group of indices to forecast July water temperatures and discharges.
- Further research into the application of flexible PCA models for summer Rhine flow and water temperature forecast. This would imply further testing, better filtering and cleaning of the data and optimisation of the model parameters; field size, number of parameters, train time and significance level.
- Testing of the principle component presented by Colman (1997) for Rhine water temperature and discharge.
- Explore possibilities for Meuse flow and temperature forecast. The Meuse is a mainly rainfed river, so flow characteristics differ from those of River Rhine.
Explore possibilities for probabilistic forecasts. Sharma (2003) and Araghinejad (2006) published interesting research on the application of probabilistic forecast models in this field. Probabilistic forecast models have an advantage over for example linear regression models that the outcome is a chance of exceedence rather than a single value. Chances can be used by water managers and industry in risk calculations.

As the large correlation between monthly average water temperature and air temperature indicates, water temperature forecast on a seasonal timescale may be considered rather a challenge to meteorologists than to hydrologists. Seasonal flow forecast more interesting for hydrologic research. Recommendations for further research in this direction are:

- A statistical analysis of the components described in the April RIZA drought report. A simple water balance model in combination with statistical relationships may make seasonal forecast possible. The large scale atmospheric or oceanic patterns may be used to fill the missing components or to describe the single components.
- Using ‘Grosswetterlagen’, defined by the Deutsche Wetterdienst (DWD), as predictors. The Grosswetterlagen are pressure fields with a minimum spatial scale of the size of Europe and a minimum duration of three days. An exploring correlation analysis found significant correlations between these patterns in winter and summer responses.
Concluding remarks

In the introduction the following research question was asked:

*How can water managers and users of cooling water be provided with forecasts, which would enable them to anticipate earlier or better to problems?*

In these concluding remarks we give our final recommendations on the design of a forecast system for cooling water problems or more general low flows and high water temperatures.

The predictive skill of the discussed techniques is limited, but forecast systems for ten day and seasonal forecast with these techniques can be developed. It is however important to communicate the uncertainties with users. This can for ten day predictions be done by publishing confidence intervals around predictions. For seasonal forecasts we would rather publish chances that water temperatures are below, around or above average. Translation of these chances into risks and possible measures could be done by industry and water managers.

The seasonal and ten day predictions could be part of an information system starting in January, which provides users with summer water temperature and discharge forecasts. The forecasts with lags from 10 days up to 3 months were not discussed in this research. Further research into these shorter term seasonal forecasts is recommended. Discharge forecasts are also interesting for the months September and October, not to the energy sector but to shipping industry. It is recommended to investigate the applicability of the discussed seasonal forecast techniques for these months.

This research evaluated statistical models for seasonal predictions and physical based models for short term predictions. Better skill may be achieved with combinations of these techniques. An example of a combined application could be a water balance model for seasonal forecast of low flow hydrology. A water temperature relationship for short term, which requires less meteorological data, could be derived with a data driven modelling approach.
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Data
Appendices
### Symbols, description and units

**Calculation of water temperature with DELWAQ**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q_n )</td>
<td>total net heat exchange</td>
<td>W.m(^{-2})</td>
</tr>
<tr>
<td>( q_{sn} )</td>
<td>net heat exchange at the air-water interface</td>
<td>W.m(^{-2})</td>
</tr>
<tr>
<td>( q_{bn} )</td>
<td>net heat exchange at the water-bed interface</td>
<td>W.m(^{-2})</td>
</tr>
<tr>
<td>( q_f )</td>
<td>heat exchange due to friction</td>
<td>W.m(^{-2})</td>
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<tr>
<td>( T_w )</td>
<td>water temperature</td>
<td>°C</td>
</tr>
<tr>
<td>( t )</td>
<td>time</td>
<td>s</td>
</tr>
<tr>
<td>( h )</td>
<td>water depth</td>
<td>m</td>
</tr>
<tr>
<td>( c_w )</td>
<td>specific heat capacity of water</td>
<td>J.kg(^{-1}).K(^{-1})</td>
</tr>
<tr>
<td>( \rho_w )</td>
<td>density of water</td>
<td>kg.m(^{-3})</td>
</tr>
<tr>
<td>( W )</td>
<td>thermal dump</td>
<td>W</td>
</tr>
<tr>
<td>( B )</td>
<td>river width</td>
<td>m</td>
</tr>
<tr>
<td>( q_g )</td>
<td>global radiation</td>
<td>W.m(^{-2})</td>
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<tr>
<td>( q_{gn} )</td>
<td>net global radiation</td>
<td>W.m(^{-2})</td>
</tr>
<tr>
<td>( \alpha_g )</td>
<td>albedo global radiation</td>
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</tr>
<tr>
<td>( q_a )</td>
<td>atmospheric radiation</td>
<td>W.m(^{-2})</td>
</tr>
<tr>
<td>( q_{an} )</td>
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<td>W.m(^{-2})</td>
</tr>
<tr>
<td>( \alpha_a )</td>
<td>albedo atmospheric radiation</td>
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<td>( \varepsilon )</td>
<td>emissivity</td>
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<td>( \sigma )</td>
<td>Stefan Boltzmann constant</td>
<td>kg.s(^{-2}).K(^{-4})</td>
</tr>
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</tr>
<tr>
<td>( CC )</td>
<td>cloud cover</td>
<td>octa</td>
</tr>
<tr>
<td>( \rho_v )</td>
<td>vapour pressure</td>
<td>mBar</td>
</tr>
<tr>
<td>( \rho_{sa} )</td>
<td>saturated vapour pressure</td>
<td>mBar</td>
</tr>
<tr>
<td>RH</td>
<td>relative humidity</td>
<td>-</td>
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<tr>
<td>LE</td>
<td>heat of evaporation</td>
<td>J.kg(^{-1})</td>
</tr>
<tr>
<td>( E )</td>
<td>rate of evaporation</td>
<td>m.s(^{-1})</td>
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<tr>
<td>( W_a )</td>
<td>wind speed at height a</td>
<td>m.s(^{-1})</td>
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<tr>
<td>( a )</td>
<td>height at which wind function is defined</td>
<td>m</td>
</tr>
<tr>
<td>( W_m )</td>
<td>wind speed at height m</td>
<td>m.s(^{-1})</td>
</tr>
<tr>
<td>( m )</td>
<td>height at which wind speed is measured</td>
<td>m</td>
</tr>
<tr>
<td>( T_{refwind} )</td>
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<td>( q_b )</td>
<td>back radiation</td>
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<td>( q_l )</td>
<td>latent heat</td>
<td>W.m(^{-2})</td>
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<td>( q_c )</td>
<td>convective heat</td>
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<td>R</td>
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<td>( \beta_g )</td>
<td>Bowen's constant</td>
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<td>( c_{wa} )</td>
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<td>J.kg(^{-1}).K(^{-1})</td>
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<tr>
<td>( T_s )</td>
<td>surplus temperature</td>
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<td>( \lambda )</td>
<td>heat exchange coefficient</td>
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### Approximation methods for short wave radiation

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<td>Iₛ</td>
<td>extraterrestrial radiation</td>
<td>W.m⁻²</td>
</tr>
<tr>
<td>Rₑₑ</td>
<td>mean distance between sun and earth</td>
<td>m</td>
</tr>
<tr>
<td>Rₛ</td>
<td>actual distance between sun and earth</td>
<td>m</td>
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<tr>
<td>β</td>
<td>rotation</td>
<td>rad</td>
</tr>
<tr>
<td>n</td>
<td>day</td>
<td>day</td>
</tr>
<tr>
<td>δ</td>
<td>declination</td>
<td>degree</td>
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<td>rotation speed</td>
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<tr>
<td>ω₁₁</td>
<td>rotation speed</td>
<td>rad.hour</td>
</tr>
<tr>
<td>L₄₄</td>
<td>day length</td>
<td>hour</td>
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<tr>
<td>Iₙₙₙₙ</td>
<td>radiation intensity at noon</td>
<td>W.m⁻²</td>
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<tr>
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<td>solar radiation at the earth's surface</td>
<td>W.m⁻²</td>
</tr>
<tr>
<td>nₙₙₙₙ</td>
<td>sun hours</td>
<td>hours</td>
</tr>
<tr>
<td>Aₐₐₐₑ</td>
<td>Angström Prescott coefficient</td>
<td>-</td>
</tr>
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<td>Aₐₐₐₑ</td>
<td>Hargreaves coefficient</td>
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<td>Bₐₐₐₑ</td>
<td>Hargreaves coefficient</td>
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<tr>
<td>Aₐₐₐₑ</td>
<td>Supit coefficient</td>
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<td>Supit coefficient</td>
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<td>Fₐₐₐₑ</td>
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### Conduction to ground layer

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<td>J.kg⁻¹.K⁻¹</td>
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<td>density of ground</td>
<td>kg.m⁻³</td>
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<td>dₙₙₙₙ</td>
<td>depth ground layer</td>
<td>m</td>
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<tr>
<td>ΔTₕₕ</td>
<td>temperature change ground</td>
<td>ºC</td>
</tr>
<tr>
<td>ΔTₚₚ</td>
<td>temperature change water</td>
<td>ºC</td>
</tr>
<tr>
<td>tₙₙₙₙ</td>
<td>length of stay</td>
<td>s</td>
</tr>
</tbody>
</table>
B Correlation maps sea surface temperatures and geopotential heights

correlation WT7 and SST1

correlation WT7 and SST2
Forecasting cooling water problems in the River Rhine

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correlation WT7 and SST3

correlation WT8 and SST1
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Appendices

- Correlation WT8 and SST2
- Correlation WT8 and SST3
Forecasting cooling water problems in the River Rhine

Appendices

correlation Q7 and SST1

correlation Q7 and SST2
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correlation Q7 and SST3

correlation Q8 and SST1
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Correlation WT7 and Z5001

Correlation WT7 and Z5002

Correlation WT7 and Z5003
Forecasting cooling water problems in the River Rhine

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Correlation WT8 and Z5001

Correlation WT8 and Z5002

Correlation WT8 and Z5003
Forecasting cooling water problems in the River Rhine

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correlation Q7 and Z5002

-1 -0.5 0 0.5 1
180°W 120°W 60°W 0° 60°E 120°E 180°W

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W

correlation Q7 and Z5001

-1 -0.5 0 0.5 1
180°W 120°W 60°W 0° 60°E 120°E 180°W

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W

correlation Q7 and Z5003

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180°W 120°W 60°W 0° 60°E 120°E 180°W

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W

90°N 72°N 54°N 36°N 18°N

180°W 120°W 60°W 0° 60°E 120°E 180°W