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Doctoral Dissertation

Jarkko Koskela

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Abstract

This thesis aims to improve knowledge of long-term inflow and streamflow forecasts. A special focus is on the development of a new long-term forecast model and on the evaluation of long-term inflow forecasts.

In the first part of the work, a new categorical long-term forecast model is developed and its performance is investigated in four case studies. The forecasts are based only on the current hydrological state of the basin and thus, weather forecasts are not utilised. By using the k-Nearest Neighbour Rule (*k*-NRR) or the minimum distance classifier (MDC), the forthcoming period is classified into a wetness class based on the hydrological state of the basin on the forecast date. Inflow forecast is finally based on this classification. The results show that for a lake with a large basin (Lake Päijänne case study), this forecast model could be used in real-time inflow forecasting and the results are comparable with the forecast accuracy of the multiple linear regression models. For small basins (<10 km^2) and in Lake Pyhäjärvi, the use of the new model for long-term discharge forecasting gave satisfactory results on April 1. On October 1, long-term forecasting turned out to be difficult irrespective of the forecast model.

In the second part of the work, long-term inflow forecasts are evaluated based on their length and accuracy. The study is based on two cases: a single multipurpose reservoir Lake Pyhäjärvi in Säkylä and a multipurpose lake-river system, River Kymijoki. The evaluation method is based on artificially generated inflow forecasts and on the optimisation of the release sequences based on these forecasts. The results are in line with the outcome of similar international studies: if the live capacity of the lake-river system compared with the annual inflow is small, short and accurate forecasts should be aimed at. For large systems, a long forecast period should be used without focusing as much on forecast accuracy. The main finding, however, is related to approximation of the potential hydropower production increase in Finland by supposing that forecast accuracy could be improved and the optimal forecast periods used. In the two case studies it was possible to increase hydropower production up to 0.7-9% compared with the status quo during the study period, if perfect inflow forecasts had been available. However, the realistic possibilities to increase hydropower production in Finland by improving forecast accuracy were approximated to be 0.5-2% at the maximum. At the same time problems related to floods and droughts would decrease.

Simulated annealing is used as the optimisation algorithm in the operation of the systems, and the evaluation of the performance of this algorithm was one of the special objectives of this study. The algorithm was flexible and reliable.

Keywords: Water resources management, hydropower, long-term inflow forecasting, pattern recognition, forecast accuracy, simulated annealing, lake-river system

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Tiivistelmä:

Työn tavoitteena on lisätä tietoa virtaamien pitkän ajanjakson ennustamisesta. Tarkemmin työssä keskityttiin uuden ennustemallin kehittämiseen ja testaamiseen sekä ennusteista saatavan hyödyn arvioimiseen.

Työn ensimmäisessä osassa kehitetään luokitteluun perustuva virtaamien ennustemalli, jonka ennustetarkkuutta tarkastellaan neljässä eri kohteessa. Mukana on kaksi pientä valuma-aluetta (<10 km^2), Säkylän Pyhäjärvi ja Päijänne. Malli perustuu hahmontunnistukseen ja valuma-alueen hydrologiseen tilaan ennustehetkellä. Sääennusteita ei hyödynnetä. Käyttämällä *k*:n lähimmän naapurin sääntöä tai minimietäisyysluokittelijaa ennustejakso määrätään luokkaan, joka kuvaa tulevan jakson kosteutta. Lopullinen (tulo)virtaamaennuste perustuu tähän luokitteluun. Tulokset osoittavat, että menetelmää voitaisiin käyttää reaaliaikaisessa virtaamien ennustamisessa Päijänteen kaltaisilla kohteilla, joilla on suuri valuma-alue ja pitkät viipeet. Mallin ennustetarkkuus kestää vertailun lineaaristen regressiomallien kanssa. Pienillä valuma-alueilla ja Pyhäjärvellä uudella mallilla huhtikuun 1. päivänä tehdyt ennusteet ovat kohtuullisia, mutta lokakuun 1. päivänä pitkän ajanjakson ennustaminen osoittautui vaikeaksi käytetystä mallista riippumatta.

Työn toisessa osassa tutkitaan ennustetarkkuuden ja ennustepituuden merkitystä ennusteista saatavaan hyötyyn. Tutkimus perustuu kahteen tapaustutkimukseen: Säkylän Pyhäjärveen ja Kymijokeen. Ensimmäinen on yksittäinen järvi, kun taas Kymijoki on monimutkainen järvi-joki – systeemi. Tutkimusmenetelmä perustuu näiden kohteiden simulointiin käyttäen keinotekoisesti luotuja, halutun mittaisia ennusteita, joilla on lisäksi haluttu tarkkuus. Tulokset ovat linjassa vastaavien kansainvälisten tutkimusten kanssa. Altailla, joiden säännöstelytilavuus on suuri vuotuiseen tulovirtaamaan nähden, tulisi käyttää pitkiä ennusteita, eikä ennusteiden tarkkuuteen tarvitse kiinnittää erityistä huomiota. Vastaavasti pienemmillä altailla pitäisi käyttää lyhyempiä ja tarkempia ennusteita. Tärkeimmät saaduista tuloksista liittyvät kuitenkin vesivoiman tuotantoon Suomessa. Toteutuneisiin juoksutuksiin verrattuna, täydellisillä ennusteilla olisi vesivoiman tuotantoa voitu kasvattaa tutkimuskohteissa 0.7-9 %. Vesivoiman lisäämismahdollisuudet Suomessa ainoastaan tulovirtaamaennusteita parantamalla arvioitiin olevan kuitenkin maksimissaan 0.5-2 %. Tarkkuuden lisääntyminen vähentäisi luonnollisesti myös tulviin ja kuiviin kausiin liittyviä ongelmia.

Juoksutusten optimointiin käytettiin työssä simuloitua jäähdytystä, jonka soveltuvuutta säännösteltyjen vesistöjen juoksutusten optimointiin samalla tarkasteltiin. Algoritmi osoittautui joustavaksi ja luotettavaksi.

Asiasanat: Vesitalous, vesivoima, pitkän ajanjakson ennustaminen, tulovirtaama, ennustetarkkuus, simuloitu jäähdytys, hahmontunnistus

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Preface

The doctoral thesis was completed at the Helsinki University of Technology (TKK) in the Water Resources Research Unit between 2003-2009 whilst working as an assistant. The research was mainly funded by the Department of Civil and Environmental Engineering but I would also like to thank Maa- ja vesitekniikan tuki ry., Tekniikan edistämissäätiö, RIL-säätiö and Sven Hallinin tutkimussäätiö for financial support.

It's been a long road to finishing this thesis. The beginning could be dated back to November 1999 when I was hired as a graduate student by the Finnish Environment Institute to maintain and develop watershed models used for hydrologic forecasting. Then, after graduating in 2002, I came to TKK to carry out post-graduate studies and it was all about forecasting. I am especially grateful for my instructor and supervisor Professor Pertti Vakkilainen, for the ideas and belief in my thesis and for those many conversations relating to the thesis, teaching and many other subjects as well. It has been a privilege to work with you. I also wish to thank docent Risto Lemmelä and professor Ibrahim Gürer for pre-examining my manuscript.

I'm also grateful for the research associates and co-workers in the laboratory for an inspiring work environment and many laughs. I'm especially thankful for Hanne Laine-Kaulio for commenting parts of the manuscript and Teemu Kokkonen, Antti Louhio and Juha Järvelä for those countless lunch breaks and conversations related to this thesis and teaching as well. MA Paula Nieminen is acknowledged for linguistic revision and my friend, Nuutti Hyvönen, for commenting on the manuscript.

Several persons, especially in SYKE, were most helpful, when I was gathering up the data. Also FMI and NCAR are acknowledged for the data received. Without the supercomputers of the Finnish IT-center of Science (CSC), the simulations would probably still be going on. I must not forget those individuals who walk through the snow survey lines all around the country year after year and gather up the invaluable hydrologic data. Without that work this thesis would never have been completed. Thank you.

My parents have always encouraged me to study, but still have not asked too often about the date of the defence. Thank you. I would also like to thank my godparents, Aira and Matti for that peaceful and welcoming home outside the hustle and bustle of the world. Your home has been a good place to collect one's thoughts. Finally, thank you Hanna. You have been most supportive and understanding about the time consumed in work and in my enthusiasms: bird-watching and football. After all, you are the one who makes me happy.

Espoo 15.5.2009

Jarkko Koskela

"It's tough making predictions, especially about the future"

- (quoted for many, including Yogi Berra)

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List of Symbols and Units

a_1	[-]	lag-1 autocorrelation coefficient
b	[€/MWh]	price of electricity
$ASWE_{Ruunapuro}$	[mm]	Areal snow water equivalent in Ruunapuro
f_t	[Mm^3]	inflow forecast for day t
F	[Mm^3]	net inflow volume forecast
Fr_{field}	[cm]	Frost depth in field
Fr_{forest}	[cm]	Frost depth in forested sites
g	[m/s^2]	gravitational acceleration
G	[€]	objective function
$GW_{Äijälä}$	[m]	state of groundwater level in Äijälä
H_i	[m]	head of the hydropower plant i
k	[-]	number of nearest neighbours used in *k*-NNR
L	[-]	number of trials at each temperature in simulated annealing algorithm
$NAO_{Dec\text{-}Feb}$	[-]	index of North Atlantic Oscillation for a season from December to February
n_{WABS}	[-]	number of days during which absolute water levels limits were violated
n_{WOBJ}	[-]	number of days during which objective water levels limits were violated
n_Q	[-]	number of days during which minimum release restriction was violated
n_{VIOL}	[-]	total number of violations
$P(\omega_i)$	[-]	probability of ω_i
$p(\mathbf{x} \mid \omega_i)$	[-]	conditional probability density function of **x** assuming ω_i
$\sum P_{May\text{-}Sep}$	[Mm^3]	Accumulated precipitation of the period preceding the forecast date (from May to September)
q_t	[Mm^3]	observed net inflow for day t
Q	[Mm^3]	observed net inflow volume of the forecast period
$\sum Q2_{Päijänne}$	[Mm^3]	Accumulated inflow to Lake Päijänne for two (2) weeks period preceding the forecast date
r	[-]	correlation coefficient
R	[m^3/s]	daily release
R_{CAP}	[m^3/s]	maximum release through the turbines

R_{LOW}	[m^3/s]	the difference between objective minimum release constraint and daily release (>0)
R_{SPILL}	[m^3/s]	the difference between daily release and maximum capacity of the turbines (R_{CAP}) (>0)
$SM_{Äijälä}$	[-]	state of the soil moisture in Äijälä (index)
T	[€]	"temperature" of the simulated annealing algorithm
W_{Abs}	[m]	absolute water level limit
W_{Calc}	[m]	simulated water level
$W_{Konnevesi}$	[m]	observed water level in Konnevesi
W_{Obj}	[m]	objective water level
α	[-]	parameter used to control the cooling velocity in simulated annealing algorithm
β	[-]	regression coefficient
γ	[-]	uniformly distributed random number Uni(0,1)
ε	[-]	normally distributed random number N(0,1)
η	[-]	coefficient of efficiency of the hydropower plant
μ	[%]	mean of the relative forecast errors
ρ	[kg/m^3]	density of water
σ	[-]	parameter for forecast accuracy
ω_i	[-]	symbol for class i

List of Abbreviations

ASWE	Areal snow water equivalent
CEP	Classification error probability
ENSO	El Niño Southern Oscillation
FMI	Finnish Meteorological Institute
k-NNR	k Nearest Neighbour Rule
MDC	Minimum Distance Classifier
NAO	North Atlantic Oscillation
NCAR	The National Center for Atmospheric Research (U.S)
PDO	Pacific Decadal Oscillation
SYKE	Finnish Environment Institute
WSFS	Watershed Simulation and Forecasting System

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1 Introduction

1.1 Hydropower, regulation and inflow forecasting

General concern about climate change and its consequences has led to an attempt to decrease the use of fossil energy sources. The beginning of the trade of CO_2-emissions in Europe in 2005 and the continuously rising world market price of oil have also guided the development into this direction. In addition to the increasing number of solar and wind energy plants, biofuel production and the use of geothermal heat, this trend has given grounds to find more efficient ways to utilise the already existing power plants using renewable energy sources. From these, hydroelectric power plants are the most significant.

In 2006, 16.4 percent of the world's electricity was produced by hydropower (IEA, 2009). In developed countries like Finland, the construction of new hydropower plants has virtually stopped because the most easily exploitable and economically most profitable sites have already been constructed. In addition, negative environmental aspects caused by man-made reservoirs impede the implementation of the unutilised capacity. This seems to be the case in developed countries all over the world (Labadie, 2004). Along with increased electricity consumption it has meant that the percentage of hydropower of the world's electricity production has decreased slowly. In Finland about 10-20% of the annual electricity production is based on hydropower. In 2004, hydropower production was 14.7 TWh (17%), whereas in 2003, it was only 9.5 TWh (11%) (Finnish Energy Industries, 2007). These differences are caused by varying hydrologic conditions.

The first hydropower plant in Finland was launched in 1891 in the town of Tampere. The largest hydropower plant (170 MW) is located in southeast Finland in the outlet of Lake Saimaa, and it was launched in the end of the 1930s. Most of the hydropower plants in Finland were constructed in the 1950s and 1960s. Today, the number of Finnish hydroelectric power plants is over 200. The combined capacity of the plants is about 3000 MW. Compared with the capacities of the Nordic neighbours, Sweden 16200 MW (Svensk Energi, 2007) and Norway 28000 MW (IHA, 2007), Finland is a rather small player in the hydropower market.

Some unutilised hydropower capacity still exists in Finland. In 2008, it was approximated that the techno-economically significant power potential is 934 MW and 2976 GWh/a (Oy Vesirakentaja, 2008). Most of this potential (569 MW) is, however, located in protected basins. By increasing the capacity of the existing power plants it is possible to increase the power potential by 261 MW. Thus, instead of building new power plants, the realistic, potential increase in hydroelectric power capacity has been seen to be based rather on modernisation of existing machinery and more effective regulation of the already existing reservoirs.

A total of 220 lake water level regulation projects have been carried out in Finland. These projects have affected some 300 lakes, which account for about one-third of the total lake area across the country (SYKE, 2007). In the early 1900s, various regulation plans were prepared in separate regulation committees. In 1934 the Waterways Regulation Office was set up by the Government (Seppänen, 1972) and the planning work was centralised. However, it was not until the end of the 1940s when regulation plans were put into action more generally. Normally, the main reasons for regulation include the increase in hydroelectric power capacity and flood protection, but the goal of release control can also be, for example, to enable waterborne traffic, log driving, recreational use of the waterways, or agriculture in nearshore fields. In any case, natural discharges are controlled by weirs and reservoirs to increase the efficiency of the utilisation of water resources for human needs and to decrease flood and drought problems. Some of the regulated lakes in Finland are man-made reservoirs, but most of them are, however, natural-born lakes. The total number of man-made reservoirs is less than 30 and they are mainly located in the west-coast basins that are sensitive to floods because of the low, natural lake percentage. Most of the lakes are rather small. The area of the lakes is normally less than 10 km^2. The largest man-made reservoirs are located in Lapland in the River Kemijoki basin. The areas of Lake Lokka and Lake Porttipahta are 417 km^2 and 214 km^2 and the live capacities are 1400 Mm^3 and 1100 Mm^3, respectively.

In recent studies (e.g. Järvinen and Marttunen, 2000; Marttunen, Hellsten et al., 2004), the economic value of the regulation for hydropower in some Finnish lake-river systems has been approximated. By regulation, it is possible to smooth seasonal variations of discharges and hence increase the efficiency of the hydropower plants. For example, the regulation of Lake Kemijärvi in the River Kemijoki basin gives an additional benefit of about 10 million Euros per year (Marttunen, Hellsten et al., 2004). The benefit results from decreased spillage in downstream power plants and the ability to shift releases to seasons where the price of electricity is higher. The value of the regulation for hydropower production in the River Kymijoki basin is approximated to be slightly under 1 M€ per year (Järvinen and Marttunen, 2000). Lately, the rising electricity prices have inevitably increased the economic value of regulation.

During the last decade, several projects have improved and updated the operation licenses of regulated lakes in Finland (Marttunen and Järvinen, 1999; Marttunen, Hellsten et al., 2004; Marttunen, Nieminen et al., 2004). Environmental aspects and effects of regulation on the recreational value of basins have been highlighted more than in the past, when flood protection and hydroelectric power production were in the focus of regulation planning. Often, as a conclusion of regulation license improvement projects, the development work and the improvement of inflow forecast systems are seen as an important part of successful regulation.

Inflow forecasts are a fundamental requirement for successful operation of lake-river systems. Reliable short-term forecasts are useful in flood protection. On the other hand, long-term forecasts can be used to optimise releases for hydropower production and to lower risks of violating both the objective and fixed maximum and minimum water level limits of the regulated lakes. Several factors affect runoff and floods and these factors differ from basin to basin around the world. Depending on the hydro-meteorological and geological properties of the basin, floods are caused by e.g. snowmelt, precipitation and dam breaks, or by a combination of several factors. In Finland, most floods are caused by snowmelt. Generally, the hydrological complexity makes inflow forecasting a challenging task. In addition, meteorological forecasts – on which inflow forecast are usually based - normally extend only a few days ahead.

Today, inflow forecasts are produced by real-time forecast systems. Increased computer capacity has led to increased use of hydrological models in forecasting. In Finland, management of the lake-river systems is often based on the hydrological forecasts produced by the Watershed Simulation and Forecasting System (WSFS) of the Finnish Environment Institute (SYKE) (Vehviläinen, 1994). The system is based on HBV-type models originally developed by Bergström (1976, 1995), and it covers the whole country. In addition, linear regression models are used in long-term forecasting to produce optional forecasts as compared with the forecasts of the WSFS.

Long-term discharge forecast models are based on long time-series of hydrologic observations on discharge and the runoff related variables. Today, most of the important, Finnish time-series are at least 40 years long. Thus, models can be calibrated and validated much more reliably than in the 1970s and 1980s when the basic ideas underlying long-term forecasting were adopted. Along with sophisticated models and longer time-series, also the systems that are used to collect the real time hydrologic data have improved and made it possible to use up to date information from the basins in real time forecasting.

This study discusses long-term inflow forecasting in Finland. The focus is on inflow volume forecasts. Other variables such as minimum or maximum discharge of the forecast period are not included in the study. The thesis covers two main topics. Firstly, a new long-term forecast model is build. The model and its performance are examined in four case studies: in forecasting the inflows to Lake Päijänne, the largest lake in the River Kymijoki basin, in forecasting the streamflow volumes in two small streams near the lake and in forecasting the inflows to Lake Pyhäjärvi, the largest lake in southwestern Finland. The new long-term forecast model is based on the current hydrologic state of the basin and on the concepts of pattern recognition. Secondly, the study concentrates on evaluating long-term inflow forecasts. The dependence between the accuracy of the forecasts and the success of the regulation is studied by using two case studies. At the same time, possibilities to increase hydroelectric power production by improving the accuracy of long-term inflow forecasts are studied.

1.2 Long-term inflow forecasting

Hydrologic forecasts can be categorised in at least three ways. Firstly, forecasts can be classified based on the forecast method. Many types of mathematical models and methods can be used to forecast hydrologic variables such as streamflow, runoff, water level and soil moisture. Secondly, the classification of the forecasts can be based on their goal. The goal can be a design value, a once in a 100 years occurring flood peak, for example, to be used in the planning and construction of a dam or dike. On the other hand, the goal can be a real-time streamflow forecast to be used for information purposes during flood and drought periods or in operation of the lake-river systems. Thirdly, forecasts can be grouped using the forecast length. If the length of the forecast period is shorter than the available weather forecast, it is usually classified as a short-term forecast. Longer forecasts can be further divided into three categories (mid-term, long-term and seasonal), but in this study, forecasts that are longer than the available weather forecasts, are classified as long-term.

Three main sources of uncertainty exist in hydrologic forecasting. Firstly, the complexity of the hydrologic phenomena and their areal variability have not been understood and modelled correctly: the forecast method may not be appropriate for the problem in question, the parameters of the model may be miscalibrated, the absence of some relevant variable may cause poor forecasts, and oversimplification of the physical model may cause significant errors. It is also possible that the method and the model used are valid but, for example, the areal precipitation used in the model is miscalculated. This can be a consequence of a sparse rain gauge or snow course network or of computational methods used to approximate the areal values.

Secondly, when using a hydrologic model for forecasting, the initial state of the model can be estimated inaccurately, which may shift into forecasts. Thirdly, a significant source of errors is inaccurate meteorological forecasts, used as input by most of the current discharge forecast models. In long-term forecasting, nonetheless, the overall need for weather forecasts depends on two things: i) How significant is the contribution of the forthcoming weather on hydrological processes and ii), how long is the lag? If the main contributors to forthcoming inflow are baseflow and/or snowmelt, weather forecasts might not be needed at all.

1.2.1 Long-term inflow forecasting methods

According to Lettenmaier and Wood (1993), long-term inflow forecasting methods can be divided into three general classes: *index-variable*, *storage accounting* and *conceptual simulation*. In addition, Lettenmaier and Wood (1993) categorise time-series models individually. Conceptual models describe all the important parts of the hydrological cycle but they use heavy simplifications in simulation (conceptualisation). The first computer aided conceptual model was the *Stanford Watershed Model* and its different versions (Crawford and Linsley, 1962, 1966) and ever since, hundreds of conceptual rainfall-runoff models have been developed. These models consist of several storages that are interconnected, recharged and depleted. The models can be lumped or highly distributed, and depending on the purpose, they can simulate different parts of the hydrological cycle by a varying accuracy. The more complicated the model, the more parameters must be calibrated and the more detailed data from the studied basin are needed. These types of models (rainfall-runoff models, snowmelt models etc.) are commonly used nowadays in real-time forecasting and the development of these models is the focus of many studies. Normally these models depend on the weather forecasts as input variables. Therefore, the performance of these models improves with improved weather forecasts. Conceptual models are also used for long-term forecasting. Because long-term weather forecasts are rarely available and often inaccurate, the so-called extended inflow forecasting procedure can be used (see e.g. Day, 1985). In this procedure, the model is set to run through the forecast period by using the actual hydrological state of the basin on the forecast day and by using observed weather data of the forecast period from the past years. If weather data are available, for example, for the last 30 years, 30 different inflow forecasts are generated. The advantage of these extended inflow forecasts is that in addition to a mean forecast, confidence limits of the forecasts are easily calculated. In Finland, real time, long-term forecasts generated by the WSFS of the Finnish Environment Institute are based on this approach.

The second class of models is based on the concept of storage accounting according to which the forthcoming discharges are determined by the amount of water in different storages of the basin on the forecast date. The discharge forecast for the period is then a linear or nonlinear function of the storages. This approach is quite similar to index-variable methods; see below. The original idea of the storage accounting models was published by Tangborn and Rasmussen (1976).

The third class of models is the index-variable models where the runoff forecasts are based on variables that are related to the forecast period runoff (snow water equivalent, soil moisture etc.) and measured prior to the forecast date. This class is composed of many types of models. Best known are the linear regression models with single or multiple independent variables. The forecast model is developed by finding a linkage between the dependent and a group of independent variables. Regression methods are mostly used for snow-fed basins, where indices for snow cover and/or winter precipitation are of primary importance (Dyhr-Nielsen, 1982). In areas where snowmelt or groundwater dominate instead of future meteorological events, methods based on the current state and water storages of the basins yield satisfactory results (Dyhr-Nielsen, 1982). Artificial neural networks are another basic example of an index-variable model used for forecasting (e.g. Salas et al., 2000). A more recently developed, long-term probabilistic forecasting model, based on a geostatistical approach (Araghinejad et al., 2006), is also an example of an index-variable method. Lately, index-variable methods have been actively updated and developed. This is a consequence of finding long-term relationships between streamflows and indices describing climate phenomena such as *El Nino Southern Oscillation* (ENSO) and *Pacific Decadal Oscillation* (PDO). Also time-series models have been used for inflow forecasting, but for real-time and especially long-term forecasting the use of different types of ARMAX models is rare. Some examples are available, however (e.g. Mohan and Vedula, 1995).

Each of the aforementioned methods has its strengths and weaknesses in long-term streamflow forecasting. The strength of the conceptual simulation and extended streamflow forecasting approach is its versatility. The same model and simulation can be used to approximate different variables. Daily values for forecast periods are available if needed. In addition, there is a straightforward approach to approximate uncertainties and confidence limits of the forecasts. However, the more complicated the model, the more parameters must be calibrated and the more difficult the model is to implement. Calibration requires plenty of data. In addition, over-parameterization can be a problem if complex models are used (see e.g. Jakeman and Hornberger, 1993). Furthermore, Lettenmaier (1984) has shown that the simulation error of the conceptual models may impose an upper limit to accuracy of long-term forecasts if update routines are not used and this limit may be less than accuracy attainable through less complex models (see also Day et al., 1985 and Lettenmaier, 1986).

The strength of the index-variable and storage accounting methods lies in their simplicity compared with conceptual simulation. Multiple regression models are easily implemented by using the most common statistical tool packages. The effective use of multiple regression methods in hydrological forecasting is discussed by Garen (1992) and some undesirable properties of the linear regression are discussed by Stedinger et al. (1988). Especially for regression models, confidence limits for the forecast can be theoretically calculated. A weakness of the linear regression method is that only one variable can be forecast by a single model and thus daily inflows, for example, are not available for reservoir management. This problem can, however, be avoided by using storage accounting models.

The World Meteorological Organisation (WMO) has co-ordinated research in order to study the performance of different rainfall-runoff and snowmelt models used for hydrological forecasting in different kinds of basins (WMO, 1975; WMO, 1986; WMO, 1992). These studies concentrated on short-term flood forecasting and on overall accuracy of the models. Observation data from different kinds of basins were used and the performance of the models was studied and compared. All models seemed to work well at least in applications most suitable for them. There has been a continuous discussion about whether to use simple models or more complicated conceptual or hydrological models in rainfall-runoff modelling and short-term forecasting (e.g. Loague and Freeze, 1985; Wilcox et al., 1990; Michaud and Sorooshian, 1994; Refsgaard and Knudsen, 1996; Reed et al., 2004). Studies related to intercomparison between different real-time long-term forecast models seem to be rare, however. WMO has been interested in long-term forecasts but different methods were discussed only in a general manner in the study published in 1982 (Dyhr-Nielsen, 1982). Druce (2001) compared the forecast accuracy of a linear regression model and a conceptual model that utilised extended streamflow procedure in long-term forecasting. The recorded real-time forecasts of the Mica project were utilised. The forecasts of the conceptual model were slightly better (Druce, 2001). Generally, there seems to be a common belief that in long-term forecasting, forecast accuracy is more affected by the available explanatory variables than the forecast method. Whichever type of model is used for long-term forecasting, it should be remembered that models should be calibrated to minimise the error in long-term flow, even if this implies large errors in simulated floods in short-term periods (Dyhr-Nielsen, 1982). When using index-variable methods this is not a problem, but conceptual models may be calibrated for flood forecasting and thus, the use of these models for long-term forecasting might be problematic.

1.2.2 Long-term inflow forecasting in Finland

The longest, still continuous water level time-series in Finland is available from Lauritsala, Lake Saimaa, since 1847. The hydrological office in Finland was set up in 1908 and since then the measurement activity extended to cover several new sites and variables. In Finland, the need for regulation and inflow forecasts was understood after the large flood in 1898-1899. In 1917 Theodor Homén (Homén, 1917) published a study on water resources management in Finland. He presented the basic principles, for example, for the regulation of Lake Päijänne and addressed the requirement for snow and precipitation observations to enable inflow forecasting and the good operation of the lake. He showed that by regulating Lake Päijänne and the lakes upstream on the basis of rainfall observations, water levels in the lakes during the 1899 flood would have been much lower. In 1923 Edvard Blomqvist published a study on forecasting high (HW) and low water levels (NW) of large lakes caused by spring floods using HW and NW of lakes upstream in several basins (Blomqvist, 1923). He also studied the forecasts on the maximum and minimum streamflows of the forecast period (NQ and HQ) based on observations of snow water equivalent and precipitation. Some of the forecasts during 1923-1931 based on these methods were published real-time and their accuracy was studied afterwards in the publication series "Tekniska Föreningens i Finland Förhandlingar" (Blomqvist, 1923-1931). However, it was not until 1936 when the first extensive study on inflow forecasting of the whole basin utilising meteorological observations was published (Siren, 1936 according to Castren, 1938). In 1938 a study on long-term forecasting in the Lake Saimaa basin by using regression analysis was published (Castren, 1938). Snow water equivalent and effective rainfall were used as independent variables when forecasting inflow volumes of a period from April to June. Also a one-month forecast period in autumn was examined. In 1945, Siren published an article (Sirèn, 1945) where he summarised the forecast methods and studies in long-term forecasting in Finland. Regression analysis was the only method used.

In the 1960s and 1970s, the development of computers first introduced the use of multiple regression analysis in inflow forecasting. The first study about the use of multiple regression analysis in forecasting the spring flood volumes in Finland was published in 1965 (Mälkki, 1965). A number of independent variables were tested but mainly snow water equivalent and precipitation were used. In 1969 Virta published a study (Virta, 1969) concentrating on inflow forecasts to Lake Päijänne by using multiple regression analysis. Extensive studies by Gürer (Gürer, 1975) give a good overview of the possibilities of multiple regression methods in Finnish conditions although the lack of data at that time made the author cautious in his conclusions. Since then it seems that only Kuusisto (1975) and Kaila (1977) have published results of the studies related to the use of multiple regression analysis in inflow forecasting in Finland.

After multiple regression methods, the use of conceptual models started to emerge. Today, the conceptual HBV model maintained by the Finnish Environment Institute is used for flood forecasting and for forecasting long-term inflows into the most important lakes in Finland (Vehviläinen, 1994). The first studies on the use of conceptual rainfall-runoff models in Finland were published by Virta (1977, 1978), Kuusisto (1977, 1978) and Vakkilainen and Karvonen (1980), although only the second paper by Kuusisto (1978) concentrated on inflow forecasting, while the others examined the overall use of these type of models in Finland. Conceptual models have been studied in several studies since then (Karvonen, 1980, 1983; Malve, 1986; Vehviläinen, 1992), but there has not been any major development in using these models in real-time inflow forecasting, since adaptive models and extended forecasts were taken into use.

Although conceptual models are currently in real-time use, multiple regression models based mainly on snow water equivalent observations are still utilised. Regression analysis is an optional method for forecasting and a source of additional information in operating regulated lake-river systems especially during spring time. Along the way, there have also been studies on different methods available for inflow forecasting. Kärkkäinen (1997) used neural networks to forecast inflow volume of Lake Päijänne for a time period of five forthcoming days. Koskela has studied the possibilities to use pattern recognition in long-term inflow forecasting (Koskela, 2002, 2004).

1.2.3 Release optimisation based on long-term inflow forecasts

Availability of long-term inflow forecasts does not ensure optimal operation of lake-river systems. Apart from several regulation related objectives, the operator must consider the uncertainties related to the available forecasts. Normally, the multi-objective nature of release policies forces the operator to use optimisation algorithms alongside with forecast models to find the release sequence that is most suitable for the forthcoming period.

Several optimisation algorithms have been used for optimal control of reservoir systems. Active research on these methods started already in the late 1950s and has continued ever since. Several thorough studies have been published about these methods (see e.g. Yeh, 1982; Labadie, 2004). Generally, two approaches are available. It is possible to use deterministic algorithms to optimise the system using historical or generated inflow time-series and then develop seasonal operating rules for the system based on the results (implicit stochastic optimisation). On the other hand, it is possible to solve a stochastic problem directly in real-time operation (explicit stochastic optimisation). In these, algorithms take directly into account the stochastic nature of the inflow forecasts.

Optimisation problems related to operating multi-reservoir systems are normally stochastic and nonlinear with continuous variables. In addition, there are usually a high number of decision variables. These characteristics often restrict the use of traditional reservoir operation algorithms such as *linear programming* and *dynamic programming* or lead to simplifications and approximations. Therefore, heuristic optimisation has emerged in the discipline. The significant advantage of the heuristic methods is that they can be directly linked with hydrologic and simulation models, without requiring simplifying assumptions in the model or calculations of derivatives (Labadie, 2004). These algorithms can not, however, guarantee an optimal solution. One example of these heuristic approaches is the *simulated annealing* (SA) algorithm.

The SA is an iterative stochastic optimisation algorithm introduced in 1983 (Kirkpatrick et al., 1983). As all heuristic optimisation algorithms, it searches the optimum from the state space by a sequence of random choices. The algorithm is motivated by an analogy to physical annealing in liquids. In an annealing process, substance is melted at a high temperature T with energy E. The liquid is then cooled down by decreasing the temperature of the system. As the cooling proceeds, the liquid becomes more ordered and approaches a steady frozen ground state. If the cooling is executed slowly enough, the liquid will obtain a crystal structure and the minimum energy at the frozen ground state. The analogy of the minimum energy state to the optimisation is the global minimum. If the cooling is executed too fast, a local minimum will be found and an imperfect crystal structure will be achieved.

The SA is widely used in different disciplines. However, very few studies have been published concerning the optimal operation of reservoir systems. Teegaravapu and Simonovic (2002) presented the context and applied the algorithm to two systems, each containing four reservoirs. The study suggested that simulated annealing could be used to obtain at least near-optimal solutions for multi-period reservoir operation problems. Mantawy et al. (2003) used a sophisticated algorithm and solved a long-term hydropower scheduling problem in a system of four reservoirs that were connected in series with improved results. Tospornsampan et al. (2005) used simulated annealing with promising results for optimisation of multiple reservoirs in a case study of the Mae Klong system in Thailand.

1.3 Value of inflow forecasts

Streamflow forecasts can be used to reduce flood damages in areas vulnerable to flooding. In addition, the biggest problems concerning droughts could possibly be avoided if forthcoming drought periods were known in advance. In addition, it seems obvious that inflow forecasts are essential for managing water resources systems efficiently. Although benefits seem evident, engineers and other officials should keep in mind that construction and maintenance of an efficient forecast system can be expensive. In addition, inevitable uncertainties related to forecasts tend to increase as the forecast period lengthens. Even if taken into account, these uncertainties affect reservoir management and make the optimal reservoir control impossible. Thus, from an engineering point of view, it is important to be able to approximate the value of a forecast system in order to avoid maintenance of a system that has no economical value, although it might be of hydrologic interest. Costs and benefits should be analysed already before the forecast system is built.

In practice, none of the regulated lake-river systems is managed without inflow forecasts. It is therefore impossible to approximate the quantitative value of the forecasts by comparing real world cases where the same system has been operated with and without inflow forecasts. Hence, the value of the forecasts and its dependence on the accuracy of the forecasts has to be approximated by using simulation models describing real-world reservoirs and basins. A general approach to evaluate inflow forecasts is to compare the operation of a reservoir or reservoirs in the case of “no forecast” and in the case of “perfect forecasts”. In addition, the dependence between the value and the accuracy of the forecasts is studied by generating an artificial random error in the forecasts and by evaluating how this error affects reservoir operation.

Several scientific articles have been published about the quantitative value of the long-term inflow forecasts (e.g. Yeh et al., 1982; Mislahani and Palmer, 1988; Takeuchi and Sivaarthitkul, 1995; Maurer and Lettenmaier, 2004). The first papers addressed the benefits from water supply forecasts for farm management (Andersen et al., 1971; Moore and Armstrong, 1976). Also the impact of forecast accuracy and operation time horizon on the success of the regulation of the irrigation reservoirs have been studied (Sivapragasam et al., 2007). A basic reference in each of the following studies and in every way notable in the research of the subject is the paper by Yeh et al. (1982). Yeh et al. studied benefits that could be gained by using long-term inflow forecasts in the Oroville-Thermalito reservoir system in California, U.S. Since then, studies have concentrated on reservoir systems in the United States but there is also a case study concerning the Mae Klong River system in Thailand (Takeuchi and Sivaarthitkul, 1995) and a case study related to the operation of the Panama Canal (Graham et al., 2006). Both single reservoir systems (Mislahani and Palmer, 1988; Kim and Palmer, 1997; Georgakakos et al., 1998) and multi-reservoir systems (Hooper et al., 1991; Takeuchi and Sivaarthitkul, 1995; Yao and Georgakakos, 2001; Hamlet et al., 2002) have been studied. Storage live capacities of the systems have varied from 0.2 times to 3.0 times the average annual inflow. Because of large live capacities, the time step of the studies has normally been a month, although there are examples of shorter time steps (Yao and Georgakakos, 2001). Inflow patterns of the studied systems have been similar compared with the Finnish conditions with a typical seasonal pattern caused by a single flood season during a year.

The approach used for comparing the cases of “perfect forecasts” and “no forecasts” is straightforward. Operation of the system is simulated either by using perfect knowledge of the forthcoming inflows or without any information and by using average net inflows as forecasts. The quantitative value of a perfect forecast can be approximated based on these simulations. On the other hand, two general approaches are available for evaluating the dependence between forecast accuracy and the quantitative value of the forecasts. The operation of the system is evaluated either by using several inflow forecast models of different accuracy (e.g. Georgakakos, 1989) or by using a synthetic inflow forecast model that can produce forecasts of varying accuracy (e.g. Yeh et al., 1982). Again, the system is operated by using these forecasts and the consequent release and water level sequences are used for evaluating the forecasts.

Based on the published studies it is obvious that the value of the forecasts depends both on the size of the reservoir and on the length and accuracy of the forecasts. However, the synthesis and comparison of the results of different studies is difficult. In addition to the dependence of the results on basin characteristics and goals of the operation, forecast accuracy can be and has been measured differently. In addition to the different basin characteristics in each study, the forms of loss or cost functions in the release optimisation of the studies have differed. Some studies concentrate only on possibilities to increase hydroelectric power production whereas others also consider the benefits of long-term forecasts for water supply, flood control etc. Sometimes these have been studied separately, however. Also the units that are considered often differ. Most of the studies have tried to approximate the economic value of the forecast, whereas some have confined themselves to some suitable variable that has no direct meaning by itself.

The update frequency of the forecast during the forecast period affects the results. It is not realistic to assume that the engineer responsible for the operation of the reservoir would use the forecast blindly until the end of the forecast period. This is true especially if the forecast and observed inflows differ substantially already at the beginning of the period. In some studies, this has been taken into account and it is assumed that the observed inflows are available immediately after they have been measured. In some studies, this effect has been considered insignificant because of the large capacity of the studied reservoir.

To conclude, the value of the long-term inflow forecasts is clearly system specific (Georgakakos, 1989; Takeuchi and Sivaarthitkul, 1995). With small reservoirs compared with annual inflow, high accuracy of short-term forecasts should be aimed at and with large reservoirs, long-term forecasts should be used without putting too much effort on accuracy (Takeuchi and Sivaarthitkul, 1995; Kim and Palmer, 1997). In large systems, better and earlier seasonal forecasts can increase benefits even by $153 million per year compared with the status quo (Hamlet et al., 2002). It seems that depending on the system characteristics, perfect forecasts could increase hydropower production by about 1-15% compared with the case of “no forecasts” (e.g. Maurer and Lettenmaier, 2004).

One of the main reasons for building up a forecast system is the possibility of providing flood warnings and reducing the economical and human losses and social suffering caused by floods. There have been studies on the benefits and costs of these flood warning systems that often concentrate on short-term forecasting (e.g. National Hydrologic Warning Council, 2002). Floods constitute a major part of the economical losses related to natural catastrophes in the world. About 500 million people are affected by floods every year.

The Commission for Hydrology of the World Meteorological Organisation has twice assigned a group to study methods available for cost/benefit analysis concerning hydrological data and forecasts (Day, 1973; WMO, 1990). The latter (Day, 1973) concentrated fully on hydrological forecasts. The state-of-the-art is fragmented judging from the final reports of these studies mainly because the cost-benefit studies executed so far have not used deep-seated approaches. However, it is obvious that flood warning systems and short-term flood forecasts have given larger benefits compared with the costs accruing from maintenance of the flood forecasting models and observation networks. Short-term forecasts fall, however, outside the scope of this thesis.

1.4 Objectives of the research

This research aims to improve knowledge of long-term inflow forecasting in Finland. The success of lake-river regulation is based on inflow forecasts and their accuracy, but also on the practices of utilising these forecasts. Although many practical reasons speak for the necessity of inflow forecasts, no studies addressing their economic value in Finland have been published. Although these kinds of studies have already been carried out under hydrological conditions similar to those in Finland and although the main results of all of these studies have been congruent, the literature review indicates, however, that the value of forecasts is very much system specific. The need for assessing the value of inflow forecasts in Finland is therefore evident. In addition, because of the alarming predictions about the consequences of climate change and rising prices of fossil energy sources, renewable energy is favoured in the developing world. Thus, an analysis is needed of possibilities for increasing hydropower production by more efficient regulation policies and by improving the forecast accuracy.

In Finland, hydrological years resemble one another. The timing of low and high runoffs rarely differs. Low flows in winter turn into floods caused by snowmelt in spring. Precipitation in summer and autumn may cause high floods but in particular summer floods are rare. The Finnish hydrological year is conservative by nature. Quite often inaccurate weather forecasts are the main cause for forecast errors in discharge forecasting. Furthermore, the growing number of scientific publications easily leads to more and more complicated forecast models and the gap between the operators and the scientists becomes wider. Thus, it is important to study whether it is possible to produce streamflow forecasts accurate enough for system operation by using simplified forecast models and the current hydrological state of the basin without weather forecasts. In addition, climate indices have been used with promising results in long-term hydrologic forecasting in different parts of the world. Thus, the possibilities of using indices describing the climate phenomena in streamflow forecasting should be studied in Finland, too.

The objectives of the study fall under two specific topics. Firstly, this study examines the performance of the developed long-term discharge forecast model that is partly based on pattern recognition. Secondly, the focus is aimed at the value of long-term inflow forecasts and its dependence on forecast accuracy. At the same time, the usability of simulated annealing in the optimal operation of the lake-river systems is assessed.

The specific objectives of the study are to:

1. Develop a long-term discharge forecast model that uses pattern recognition as an aid in forecasting and does not use weather forecasts as an input, and assess the performance of this model.
2. Assess how far ahead it is possible and reasonable to forecast inflows and discharges in Finnish conditions and identify characteristics affecting this forecast length.
3. Assess the economic value of the long-term inflow forecasts and how the value is dependent on forecast length, accuracy and update frequency. At the same time, determine at which point the increasing errors of the forecasts overtake the additional value of the longer forecast period.

4. Approximate the realistic possibilities to increase hydropower production in Finland by improving the accuracy of long-term inflow forecasts.
5. Assess the possibilities of simulated annealing in optimisation of the operation of the lake-river system.

The study consists of two main parts. In the first part, a long-term inflow forecast model is built. The main goal is to forecast inflows into Lake Päijänne, located in the upper part of the River Kymijoki basin and into Lake Pyhäjärvi in southwestern Finland. In addition, streamflow forecasts for two small catchments located just upstream of Lake Päijänne are studied. In the second part, inflow forecasts are evaluated in two different locations in Finland, in Lake Pyhäjärvi and in the River Kymijoki basin. The former is a case study of a single multi-purpose reservoir and the latter is a complex multi-purpose reservoir system. Finally, the results of the two parts of the study are combined. The value of the new model in real-time long-term forecasting is assessed based on the results of the latter part of the study.

2 Research basins and hydrologic observations

2.1 River Kymijoki and Lake Päijänne

River Kymijoki is one of the biggest and economically one of the most important rivers in Finland. It flows in south and southeast Finland from the outlet of Lake Päijänne through the lakes Ruotsalainen and Konnivesi to Lake Pyhäjärvi [1 and ahead until it reaches the Baltic Sea. The river is utilized many ways with hydroelectric power production being one of the most important. Nowadays, twelve hydroelectric power plants are located in River Kymijoki. The combined maximum capacity of the plants is about 215 MW and the average annual electricity production about 1.3 TWh. This is about 9% of Finland's annual hydroelectric power production.

River Kymijoki is important also because of its ecological values and recreational use. About 350000 people are living in the towns around the lake-river system and about 9000 summer cottages and other buildings are located near the shores (Marttunen and Järvinen, 1999). Fishing and canoeing are very popular throughout the watercourse, as well. In addition, the basin is important for water supply. Water from Lake Päijänne is transported through an underground tunnel to be used in Helsinki city area and water is also used in the forest industry plants.

Because of the interesting nature and importance of River Kymijoki and Lake Päijänne, several studies have focused on the basin. Already in 1917, Homén (Homén, 1917) planned the basic principles for the regulation of Lake Päijänne. An integrated water resources development plan for the basin was published during 1972-1981 (National Board of Waters, 1972a, 1972b, 1977, 1981). More recently Jolma applied a support system for the real-time operation of Lake Päijänne and River Kymijoki (Jolma, 1999) and the regulation licenses of the lake-river system have been updated (Marttunen and Järvinen, 1999; Järvinen and Marttunen, 2000). These are only a few examples of the studies related to Lake Päijänne and River Kymijoki.

The area of the river basin is 37159 km^2, which is about 11% of the area of the whole country. The lake percentage of the River Kymijoki basin is 18.3 (Eskola, 1999). Water flows from north to south but the length of the river is difficult to assess because it empties into the Baltic Sea in five different streams near the towns of Kotka and Pyhtää. However, the length of the river from the outlet of Lake Päijänne in Kalkkinen to Ahvenkoski, the most western outlet of the river, is 203 km. The head between Lake Päijänne and the Baltic Sea is about 78 m. During 1961-1990 the average annual precipitation varied in the basin from 674 mm in the northern parts to 727 mm in the southern parts (Hyvärinen et al., 1995). At the same time the annual actual evapotranspiration varied between 359 mm and 455 mm. The maximum annual snow water equivalent in the areas near Lake Päijänne has varied during 1958-2006 between 36 mm and 210 mm, the average being about 114 mm. The regulation of the Kymijoki lake-river system began in 1959 when the Vuolenkoski power plant in the outlet of Lake Konnivesi was completed. Today, the Ministry of Agriculture and Forestry or the Southeast Finland Regional Environment Centre are the holders of the operation licenses of the most important lakes. The latter is authorised by the Ministry of Agriculture and Forestry to be responsible for the regulation. A map of the basin is presented in Figure 1 and a detailed map of the northern sub-basins in Appendix A.

1) Lake Pyhäjärvi is a very common name for a lake in Finland. In this thesis two such lakes are discussed. Lake Pyhäjärvi in Iitti in the River Kymijoki basin and Lake Pyhäjärvi in Säkylä in the River Eurajoki basin.

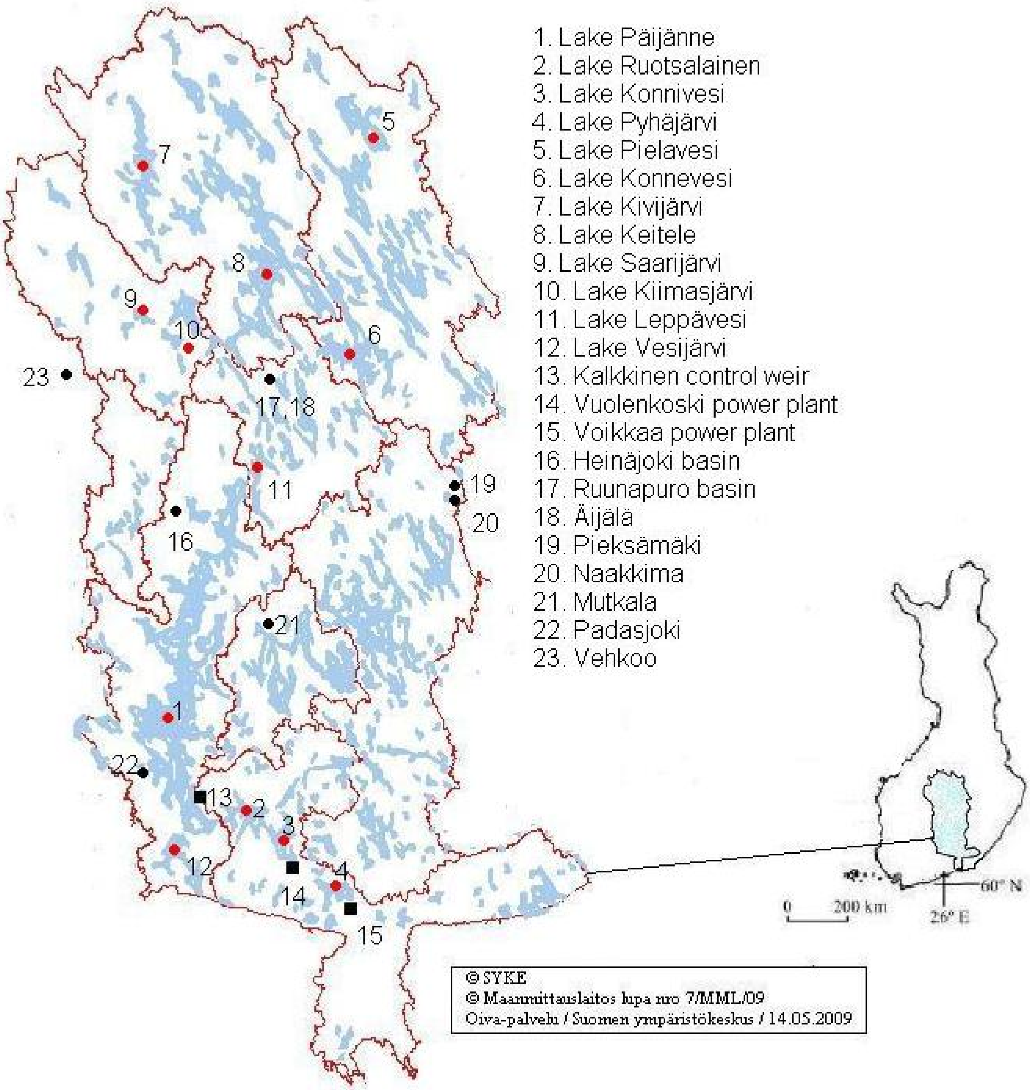


Figure 1. The River Kymijoki basin

Lake Päijänne, located in the River Kymijoki basin, is the second largest lake of the country. The drainage area of the lake is about 26480 km^2 and the area of the lake about 1100 km^2 with more than 1800 islets. The lake percentage of the Lake Päijänne basin is 19.5. Compared with other Finnish lakes, Lake Päijänne is also exceptionally deep with an average depth of 16.2 m. Since 1964, Lake Päijänne has been regulated by using a control weir in Kalkkinen for the purpose of flood prevention and to increase the hydropower potential downstream and make conditions more suitable for waterborne traffic. Also the canal of Kalkkinen can be used for regulation. However, about 70% of the outflow of the lake runs through the natural cascade in Kalkkinen and this outflow cannot be controlled. The live capacity of the lake is about [2] 1600 Mm^3, which is about 22% of the annual inflow. The average annual net inflow to Lake Päijänne is presented in Figure 2. About 62 percent of the inflow comes from Lake Leppävesi, about 12% from the Jämsä and Sysmä watercourses, and about 17% flows from the areas near the lake. The rest of the inflow comes directly as precipitation into the lake (National Board of Waters, 1981). Some of the lakes upstream of Lake Päijänne are regulated, but their live capacities are modest.

2) Approximated by using NN+77.35 – NN+78.80. Water levels in this thesis are given either in the national height system NN or N43.

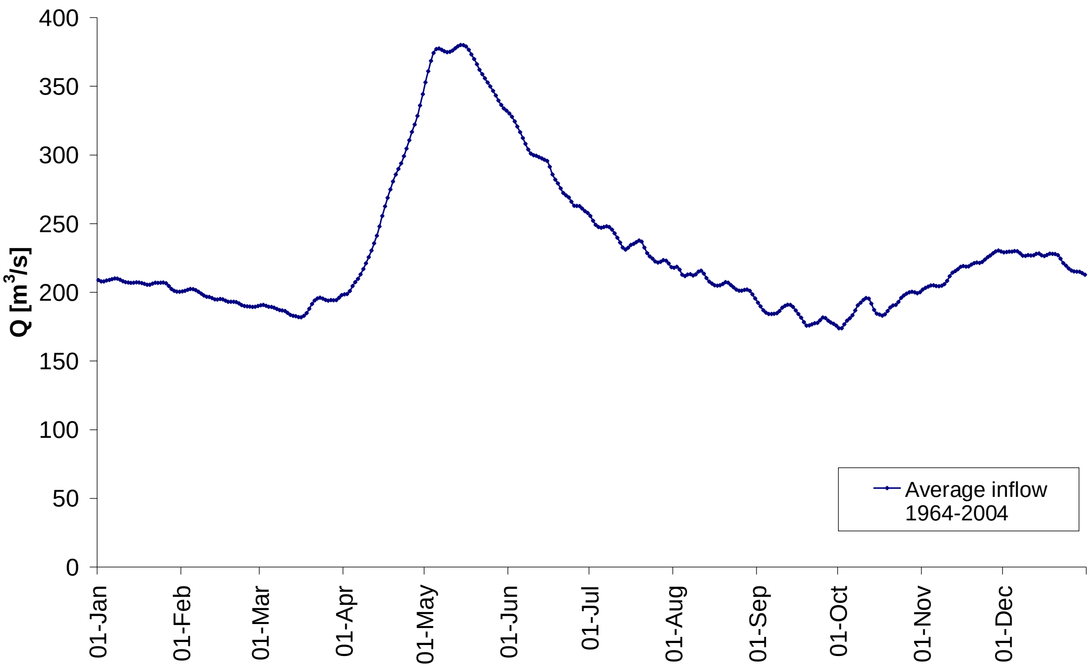


Figure 2. Mean net inflow to Lake Päijänne.

The water level of Lake Päijänne has been measured in Kalkkinen located near the outlet in the southern part of the lake daily since 1880. In 1910, another water level station was opened in Haapaniemi in the northern part of the lake. Because of the large area, water levels in different parts of the lake are not equal. Therefore, the average of the readings in these two stations was used as a daily water level in simulations of this work assuming that both observations were available. The outflow has been observed since 1911 in the outlet in Kalkkinen gauging station. River Kymijoki emerges from this outlet from which it first flows to Lake Ruotsalainen.

The area of Lake Ruotsalainen is about 80.7 km^2 and its average depth is about 11 m. The lake is connected with Lake Konnivesi via the Jyrängönvirta stream. The area of Lake Konnivesi is about 50.4 km^2 and its average depth is 14 m. The volume available for the regulation is 110 Mm^3 in Lake Ruotsalainen and 60 Mm^3 in Lake Konnivesi, respectively. The water level of Lake Ruotsalainen has been measured daily since 1900 and that of Lake Konnivesi since 1908. Discharge observations from Vuolenkoski in the outlet of Lake Konnivesi are available since 1908 but discharges in Jyrängönvirta stream are not observed systematically.

Lake Ruotsalainen and Lake Konnivesi are relatively small lakes compared with their annual inflow and hence they could be described as run-through lakes. The residence time of the lakes is only 40 days. In addition to outflow from Lake Päijänne, only a small lateral stream flows into Lake Ruotsalainen. However, the runoff from Rääveli watercourse flows into Lake Konnivesi with the average discharge of 7 m^3/s. The water levels and release of these lakes are controlled by using the dam of the hydroelectric power plant in Vuolenkoski. The plant was built at the end of the 1950s and the regulation of the lakes began at the same time. Downstream of the Vuolenkoski plant, only a single power plant in Mankala is located in the river before it flows into Lake Pyhäjärvi in Iitti.

Lake Pyhäjärvi in Iitti is a small, regulated lake. A weir in its outlet in Voikkaa is used to control the releases to River Kymijoki and thus to control the inflows to the chain of the biggest power plants in the river course. The water level of the lake has been measured daily since 1901 and discharges in Voikkaa since 1964. In addition to the inflow from the main stream, the runoff from Mäntyharju watercourse with the average discharge of 39 m^3/s flows into Lake Pyhäjärvi. Some statistics of the most important lakes of the Kymijoki lake-river system are collected into Table 1. The total live capacity of the lake-river system is only about 25% of the inflow to Lake Päijänne and it is mainly concentrated in Lake Päijänne. However, the storage capacity of the lakes downstream can be used to small-scale flood prevention and their state should be taken into account in the operation of Lake Päijänne.

Table 1. Statistics about the reservoirs in the River Kymijoki basin.

Lake	Area of the lake [km^2]	Average depth [m]	Max. depth [m]	Live storage capacity [Mm^3]	Regulated since	Average water level (1965-2004) NN+[m]
Lake Päijänne	1100	16.2	95.3	1600 2)	1964	78.16
Lake Ruotsalainen	80.7	11	55	110 3)	1959	77.40
Lake Konnivesi	50.4	14	36	60 4)	1959	77.28
Lake Pyhäjärvi, Iitti	80	4	22	25 5)	1977	65.28

2) Approximated by using NN+77.35 - NN+78.80

3) Approximated by using NN+76.20 - NN+77.65

4) Approximated by using NN+76.20 - NN+77.40

5) Approximated by using NN+65.10 - NN+65.40

2.2 Small experimental basins

Two small experimental basins are located just upstream of Lake Päijänne. The Ruunapuro basin is located north of Lake Päijänne and its area is 5.39 km^2. The area of the second basin, Heinäjoki, is 9.4 km^2 and it is located on the west-side of Lake Päijänne. Both of the basins are part of a large hydrologic study started at the end of the 1950s. The study renewed Finland's runoff observations network and started the measurement activity in about 30 new small drainage basins. During the first years Mustonen (1965a) and Mustonen and Seuna (1969) analysed and published the data for all these basins. Several hydrologic variables have been measured in both of the basins since 1958.

Runoffs are measured by using overflow weirs where water levels are observed by using limnigraphs. Because the operation of a limnigraph is occasionally uncertain, especially during winters, some of the runoffs are interpolated based on the weekly water level observations taken by the officials, on the rain and temperature data and on the runoff observations in the comparison catchments. Daily runoff values are available from the Ruunapuro basin since January 1 1958 until the end of September 2006. From the Heinäjoki basin, runoff measurements are available since January 1

1958 until September 9 2000. Some basin characteristics of the small catchments are given in Table 2. The lake percentage of the basins is close to zero.

Table 2. Characteristics of the small research basins (Mustonen, 1965b).

Research basin	Drainage area [km^2]	Mean land slope [%]	Percentage of cultivated area [%]	Percentage of peat land [%]	Percentage of coarse soils [%]
Ruunapuro	5.39	6.4	22	10	53
Heinäjoki	9.40	7.6	8	10	62

Based on the comparison of the maps from 1965 (Mustonen, 1965a) and today, no big changes were observed in the area of cultivated land during the last 40 years. Judging from the notes in the snow course measurement prints, there have been some spotty felling activities in the basins during the years. However, these are not considered large enough to cause significant changes in the runoff. The mean discharges of the streams are presented in Figure 3. In addition to the discharge measurements, frost and snow depth, snow water equivalent and some meteorological data have been measured in the basins since 1958.

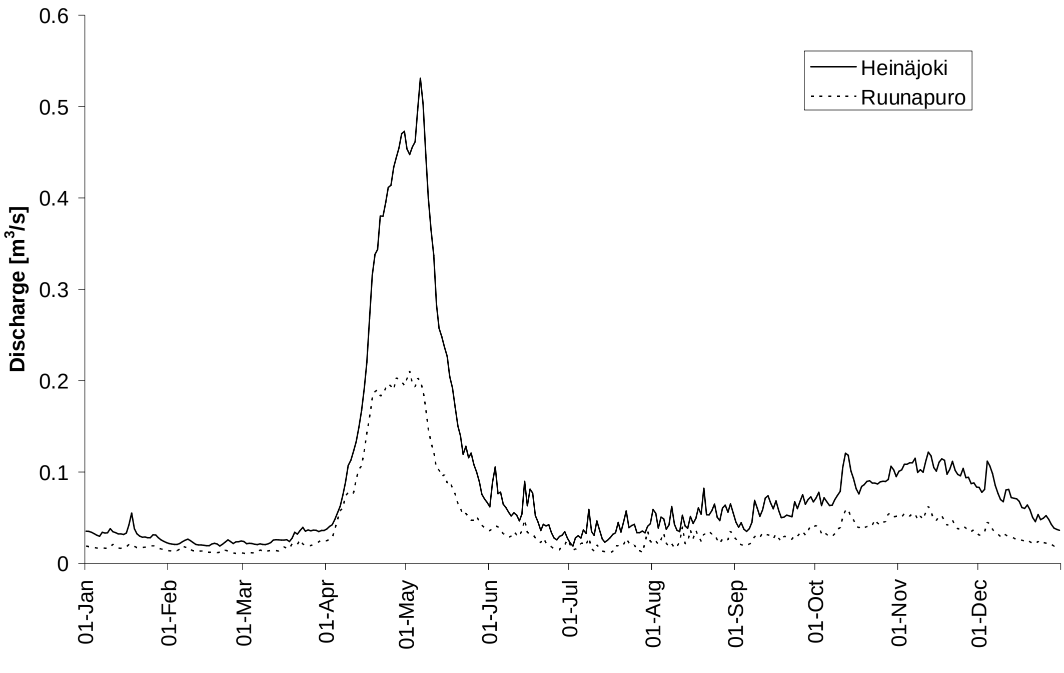


Figure 3. Mean discharge in Ruunapuro (1958-2005) and Heinäjoki (1958-2000).

2.3 Lake Pyhäjärvi in the River Eurajoki basin

Lake Pyhäjärvi in Säkylä is located in the River Eurajoki basin and it is the largest and most important reservoir in southwestern Finland. River Eurajoki emerges from Lake Pyhäjärvi, flows through three towns, Eura, Kiukainen and Eurajoki, and empties into the Gulf of Botnia 53 km from the lake. The area of the lake basin is 614 km^2 and the area of the lake about 154 km^2. Two main rivers empty into Lake Pyhäjärvi, namely River Yläneenjoki and River Pyhäjoki. The area of the River Yläneenjoki basin is 215 km^2 and the area of the River Pyhäjoki basin is 81 km^2. A map of the River Eurajoki basin is presented in Figure 4. A large part of the Lake Pyhäjärvi basin is covered by forests and about 20% of the basin (lake itself not included) is cultivated. The annual average areal maximum snow water equivalent in the region near the lake has been about 74 mm since 1965. During 1961-1990 the average precipitation was about 703 mm/year and the average actual evapotranspiration based on the water balance studies 463 mm/year in the River Eurajoki basin (Hyvärinen et al., 1995).

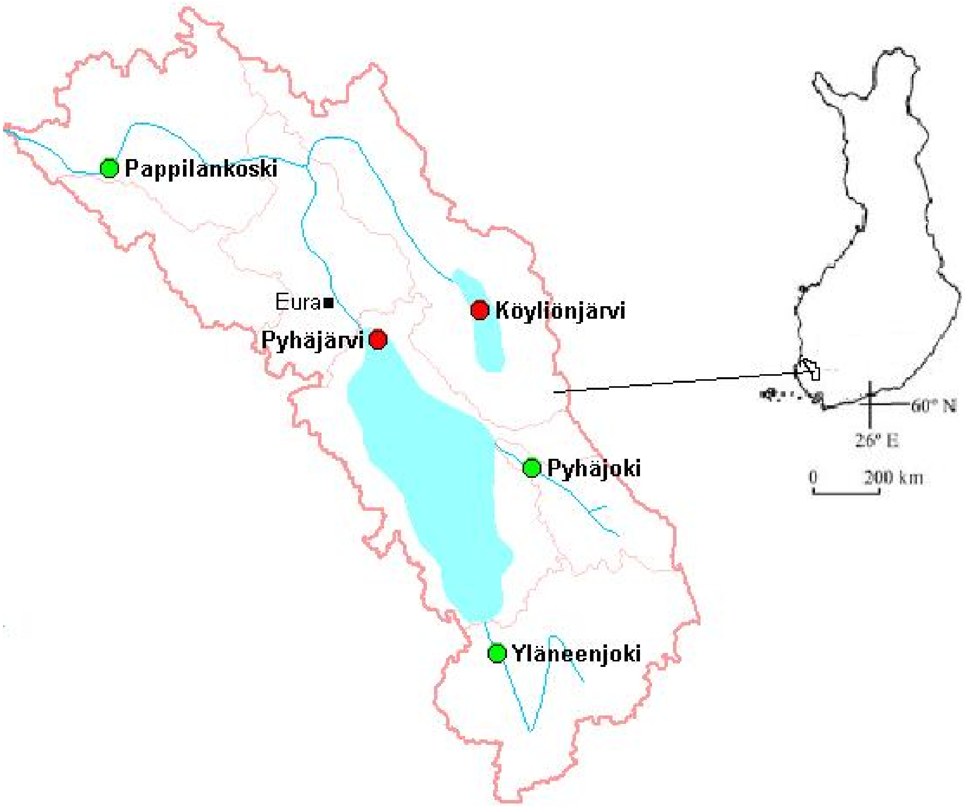


Figure 4. The Lake Eurajoki basin (© Finland's Environmental Administration, printed with permission).

The lake has been regulated since 1975 by using a control weir in the outlet of the lake (Figure 5) mainly for three purposes: flood prevention, efficient hydroelectric power production and to assure water supply downstream. However, since 2000 the Kauttuankoski power plant has not been in use, but the lake is still regulated. The volume of the lake is about 850 Mm^3 and the live storage capacity is 89 Mm^3. The lake is large if it is compared with the average inflow (4.9 m^3/s). The live storage capacity is about 57% of the annual inflow. The flood season is caused by snowmelt in spring, and during summers high evaporation rates often overtake the river inflows causing negative net inflows. A subsurface flow from Lake Pyhäjärvi to Lake Köyliönjärvi may also decrease the net inflows. The net inflows normally increase again towards autumn because of decreasing evaporation. The water level of the lake has been measured since 1914 and the discharge in the outlet since 1965. Therefore, it is possible to approximate the inflows into the lake properly since 1965 by using the water balance equation. The average net inflow is presented in Figure 6.

Figure 5. A view to Lake Pyhäjärvi and the regulation weir in Kauttuankoski.

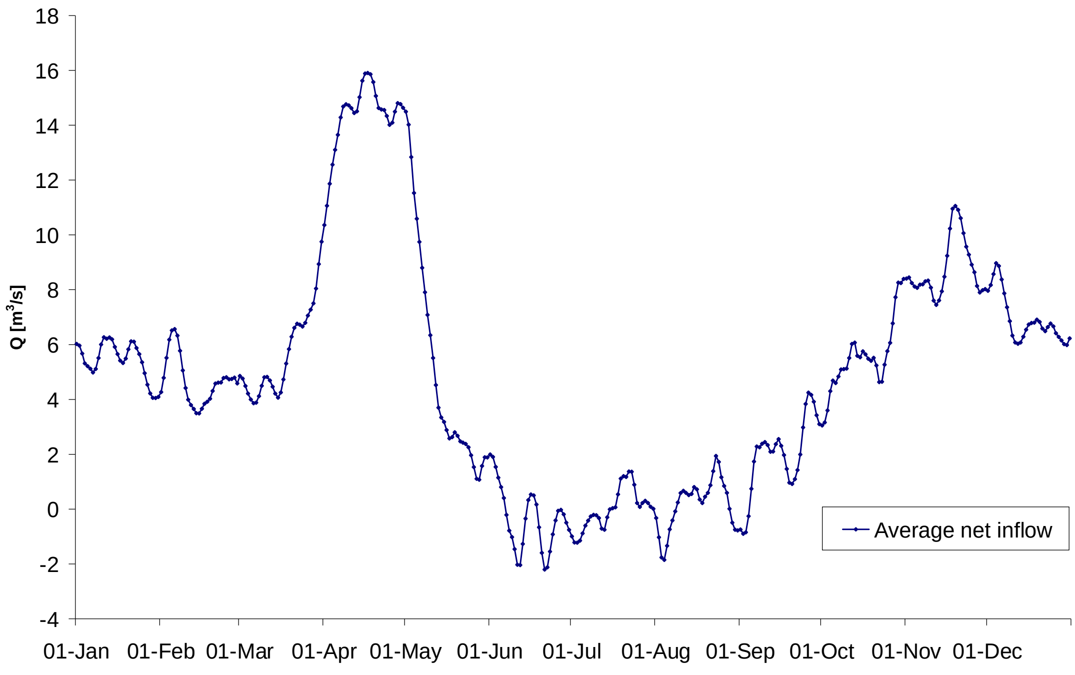


Figure 6. Mean net inflow to Lake Pyhäjärvi of a period between 1966 and 2004.

2.4 Inflow

To evaluate the inflow forecasts and to assess the accuracy of the forecast model, inflow observations are needed. Unfortunately, the inflow into a lake cannot be measured directly because of scattered runoff, but fortunately based on the other hydrological observations the net inflow can be approximated. By using the water level and outflow observations with the known connection between the volume, the area and the water level of the lake (WAV curve), the inflows can be calculated by using the water balance equation,

$$I - O = \frac{dS}{dt}, \qquad \textbf{(2-1)}$$

where I is the net inflow, O is the outflow, dS is the change of the volume of the water storage in a time step dt. The average daily values are used. A shorter time step cannot be used because most of the data of this study have been registered into the databases as daily averages on a daily basis. In addition, the time horizon of the study is months and thereby it is not reasonable to use shorter time steps.

When the water balance equation is used to approximate a net inflow, the variability of the calculated daily inflow series may be large. In other words, the net inflows between two consecutive days can be very different. In addition to precipitation and evaporation, the variability is based on the water level changes caused by wind and air pressure. Small errors in the observations, especially in the water level measurements, could also cause the phenomenon. To avoid problems in the simulations, the inflow time series were smoothed by using the Lowess smoothing algorithm (Cleveland, 1979). A locally weighted regression with “tricube” weight function and a free software package (W.S. Cleveland (1985) Bell Laboratories Murray Hill NJ 07974) were used. The daily averages of the calculated smoothed inflows to Lake Päijänne and Lake Pyhäjärvi are presented in Figure 2 (page 32) and in Figure 6 (page 36).

2.5 Data available for long-term forecasting

In addition to weather forecasts, some variables describing the current hydrologic state of a basin can be used to estimate the volume of the inflow or streamflow of a following period. Snow water equivalent, frost depth, the state of groundwater and soil moisture storages could be used. In addition, accumulated discharges and precipitation of the periods preceding the forecast date and water levels of upstream water storages may be useful when forecasting inflows and discharges of the following period.

Daily inflows to Lake Päijänne can be approximated since 1911 and inflows to Lake Pyhäjärvi in Säkylä since 1965. Runoffs in the small catchments have been measured since 1958. Unfortunately, all the hydrological time series are not as long and extensive. The following observations were available, however, and were studied as possible variables to explain the forthcoming inflow volume of Lake Päijänne and Lake Pyhäjärvi and the streamflows of the small catchments.

2.5.1 Snow water equivalent

Several snow survey lines are observed in the Lake Päijänne basin. Observations from these lines are recorded about twice a month and the observations are used to approximate the areal snow water equivalent in the different sub-basins. The Lake Päijänne basin is divided into several sub-basins of which three sub-basins in the north (Rautalampi, Viitasaari and Saarijärvi), are especially large (see map in Appendix A). One of the values is an approximation of the snow water equivalent in these three sub-basins. This value has been calculated since 1958. Another describes the snow water equivalent in the areas near Lake Päijänne and it has been calculated since 1951.

In the Ruunapuro and Heinäjoki basins, the areal snow water equivalents have been calculated by using the snow survey line measurements since 1958. The location of the snow course of the Ruunapuro basin was changed in the early 2000s. It is assumed in this work, however, that this relocation has not significantly affected the areal approximation. In the Lake Pyhäjärvi basin, an areal snow water equivalent approximation describing the areas near the lake is available from 1958 until 2006. As above, this areal value is based on the snow survey line measurements.

2.5.2 Water levels of the lakes in the upper course

Several lakes are located in each of the large watercourses located upstream of Lake Päijänne and the runoffs from these basins are sources for the inflow of Lake Päijänne. Thus, the water levels of the largest lakes in the upper course could be used to forecast the inflows of Lake Päijänne. These were also used for forecasting by Blomqvist already in 1923 (Blomqvist, 1923). The water level observations are available as follows: Lake Leppävesi (1911-2006) and Lake Vesijärvi (1910-2006) just upstream of Lake Päijänne, Lake Kivijärvi (1911-2006) and Lake Keitele (1911-2006) in the Viitasaari watercourse, Lake Saarijärvi (1911-2006) and Lake Kiimasjärvi (1967-2006) in the Saarijärvi watercourse, Lake Pielavesi (1934-2006) and Lake Konnevesi (1911-2006) in the Rautalampi watercourse. The areas of the lakes are respectively: Leppävesi 65 km^2, Vesijärvi 108 km^2, Kivijärvi 156 km^2, Keitele 502 km^2, Kiimasjärvi 4 km^2, Saarijärvi 14 km^2, Konnevesi 187 km^2 and Pielavesi 111 km^2. All the locations are presented on the map in Figure 1 (page 31).

Lake Pielavesi and Lake Konnevesi are unregulated and therefore the water levels of the lakes are fit for discharge forecasting downstream. The regulation of Lake Keitele is almost unnoticeable. Instead, Vesijärvi, Kivijärvi, Kiimasjärvi, Saarijärvi and Leppävesi are regulated. The operation licence of Lake Leppävesi has not been significantly changed since the beginning of the regulation in 1961. The regulation rule for Lake Kivijärvi was updated in 1957. The operation licences of the two regulated small lakes in the Saarijärvi watercourse have also been changed. The licence of Lake Saarijärvi changed in 1975 and the licence of Lake Kiimasjärvi in 1982. Lake Vesijärvi located in the southern side of Lake Päijänne has been regulated since 1975.

The lake percentage of the small experimental basins is very small. This is due to the fact that the selection of test basins into the hydrological network in Finland in the 1950s was partly based on small lake percentage. Therefore, water levels of the upstream lakes can not be used to explain the forthcoming streamflow in Ruunapuro and Heinäjoki. This is the case also in Lake Pyhäjärvi.

2.5.3 Groundwater and soil moisture

Groundwater levels give valuable information about the water balance of soil. Unfortunately, they have not been observed systematically in Finland until the 1960s when the officials in the different road districts began to carry out measurements. In the 1970s, also the Regional Environment Centres began to co-ordinate activities to measure water level changes in soil. Several groundwater level gauging stations are located in the Lake Päijänne basin and nearby. The road district maintained stations from autumn 1961 until 1994 in Padasjoki and in Pieksämäki: a single standpipe was used to measure the groundwater level. Since 1975 until now, groundwater levels have been observed in Mutkala, Äijälä and Naakkima by the Regional Environment Centres. Äijälä is located right next to the Ruunapuro basin and the other two stations are located east of the lake. In addition, groundwater levels in Vehkoo, west of the Lake Päijänne basin, are available since 1975. Also other groundwater gauging stations are located in the Lake Päijänne basin but the ones presented are considered to give a typical and adequate sample of the groundwater levels in the area. A single gauging station upkept by the Environment Centres is composed of about 10 standpipes and the average of the readings in these pipes is used as a daily groundwater level observation. Again, locations of the groundwater stations can be seen on the map in Figure 1. In the Lake Pyhäjärvi basin, a groundwater gauging station is located in Oripää, west-southwest of the lake. The observations are available from 1970 until 1999.

In the Äijälä groundwater station near the Ruunapuro basin, measurements of soil moisture have also been recorded by using neutron probe tubes during 1980-1992. Readings from eight different tubes down to 400 cm below the soil surface every 10 cm are available. Unfortunately, time-series are scattered. The readings are from different dates each year and some of the values are missing. However, it is possible to get an idea about the usefulness of soil moisture data in long-term forecasting in small basins by comparing this data with the streamflow volumes of Ruunapuro.

2.5.4 Discharge and frost

In the studies of Mustonen (1965b) concerning the effects of the meteorological and basin characteristics on runoff, frost depth on March 31 was a statistically significant independent variable in the linear regression models. The models were used to forecast firstly spring runoff and secondly summer and autumn runoff. The signs of the regression coefficients were negative in both cases. On the other hand, Gürer (1975) stated that the inclusion of the frost thickness into the regression models for the annual flow for several small basins did not improve the models that were set up by the annual corrected precipitation. When considering the rainfall-runoff processes, frost depth is a difficult variable. A low frost depth can be expected, if the snow layer is thick. This would cause a negative sign in the regression coefficient when forecasting spring runoffs. On the other hand, a thick frost can increase the infiltration excess overflow during the snow melt season and the effect in the regression model may be the opposite.

In the Ruunapuro and Heinäjoki basins, the frost depth has been measured since 1958. The measurements are made on the same days as the snow measurements and at the same snow course lines. For the early years, however, only a few observations are available each winter. During the first years, the observations were made by using a rod of steel that was hit into the ground and flipped. Later the frost observations have been based on the readings of the methylene blue tubes. The latest observation preceding the forecast date is used for forecasting in this work.

The accumulated inflow and streamflow of the period preceding the forecast date is also considered as a possible variable to explain the forthcoming discharge. A time period of two or four weeks preceding the forecast date is used. This variable could describe the hydrological state of the basins in at least two ways. If early spring occurred, snow melt would have already begun on the forecast day and discharges during April might be larger compared with a year with an average timing of snowmelt. On the other hand, the discharge sum could provide information about the soil water balance in the area because a great part of the winter runoff is based on baseflow.

2.5.5 Precipitation

The available values of areal precipitation in different basins are based on the precipitation network of the Finnish Meteorological Institute (FMI) (Venäläinen et al., 2005). The areal values are available for 10×10 km^2 grids. For the small basins, Ruunapuro and Heinäjoki, areal values are available since 1961. In the Lake Päijänne basin, the daily areal precipitation is available for the period between 1971 and 2000. Similar data are also available for the Lake Pyhäjärvi basin for the period between 1971 and 1999. The idea is not to use forthcoming precipitation in inflow forecasting. Instead, the accumulated precipitation of the period preceding the forecast date is used. The decision about which variable to use and the length and timing of the period is based on correlation analysis.

2.5.6 North Atlantic Oscillation (NAO)

Nowadays, also the indices describing the global climate phenomena such as El Niño Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) are used in long-term discharge forecasting. In addition, indices of *North Atlantic Oscillation* have been used as an independent variable in studies of streamflow variability (Cullen et al., 2002; Rimbu et al., 2002; Danilovich et al., 2007). The concept of relating the climate data to the forthcoming floods is not new, however. Already in 1927-1928 Bliss published a study considering the Nile floods and world weather (Bliss, 1927-1928). In recent studies, the results have been promising both in using the indices as independent variables in multiple regression models (Hsieh et al., 2003) and in classifying and specifying extended streamflow forecasts (Hamlet and Lettenmaier, 1999). The climate indices have been used for streamflow forecasting all over the world: for example, in Australia (e.g. Piechota et al., 2001), in the United States (e.g. Hamlet and Lettenmaier, 1999; Piechota et al., 1999; Hsieh et al., 2003) and in both Iran (Araghinejad et al., 2006) and Turkey (Sen et al., 2004). However, further studies are needed about the possibilities of the global climate indices in the long-term streamflow forecasting in Finland.

The North Atlantic Oscillation (NAO) is a climatic phenomenon in the North Atlantic Ocean. The NAO refers to swings in the atmospheric sea level pressure difference between the Arctic and the sub-tropical Atlantic. As NAO affects the mean wind speed direction, it also alters the seasonal mean heat and moisture transport between the Atlantic and the neighbouring continents (Hurrell et al., 2003b). Lately it has been related to various hydrologic phenomena and also to hydrologic forecasting. Uvo and

Berndtsson (2002) showed the linkage between NAO and hydropower availability in Norway, Sweden and Finland and furthermore, Cherry et al. (2005) focused on revealing the impacts of NAO on Scandinavian hydropower production and energy markets. Nilsson et al. (2008) studied the usability of the forecasts of the Global Circulation Models for long-term streamflow forecasting in Norway and Sweden. This work set out to study whether the temporal variations of the NAO phenomenon could be used to forecast long-term inflows into Lake Päijänne and Lake Pyhäjärvi and streamflow in the two small catchments. The seasonal index of the NAO based on the difference of the normalized sea level pressures between Ponta Delgada, Azores and Stykkisholmur/Reykjavik, Iceland since 1865, is available from NCAR (NCAR, 1995). In this study, the seasonal (three months) station based NAO indices are used. Positive values of the index indicate stronger-than-average westerlies over the middle latitudes and warm and moist conditions in Scandinavia.

3 Long-term inflow forecast model

In Finland, low winter discharges typically turn into floods caused by snowmelt in April-May. The mean precipitation sum is highest during the summer months, but summer floods are rare. Discharges increase towards autumn because of decreasing evapotranspiration, but floods in autumn are not as common and normally not as strong as the spring floods caused by snowmelt. During 1961-1990, the mean annual precipitation was about 660 mm and the annual evapotranspiration about 341 mm (Hyvärinen et al., 1995). The variability between different years is moderate. This typical pattern of the Finnish hydrological year is utilised in a new long-term inflow forecast model of this work. Forecasts are based on the current hydrological state of the basin; weather forecasts are not used. One of the main goals of the study was to construct a forecast model that can be used to forecast streamflow and especially inflows up to six months ahead.

To assess the model, its accuracy is studied on two forecast dates in four case studies. To study the possibilities to forecast spring and summer runoffs, April 1 is used as a forecasting day and the forecasts extend up to a six-month period, i.e. until the end of September. On average, inflows start to increase in southern Finland around the turn of March to April. For the effective operation of a large lake-river system, forecast for the spring flood season should be available earlier. For long-term forecasting that concerns the spring and summer inflows, however, the data available at the end of March probably contain the best information available. To evaluate the possibilities of forecasting runoff and inflow in autumn and winter, October 1 is used as a forecasting day. Normally, runoffs start to decrease in late autumn and winter runoffs are stable until the snowmelt starts to increase runoffs in late March or early April. Again, forecasts of the length of 1-6 months are generated and their accuracy is studied.

The main objective is to forecast the inflows to Lake Päijänne and Lake Pyhäjärvi, but the success of the model is also studied by forecasting the accumulated streamflow of two small streams located in the Lake Päijänne basin. The accuracy of the model is first studied in Lake Päijänne meaning that a basin with a large lake percentage and long delays in the basin is investigated. The net inflow to Lake Päijänne is partly regulated. The live capacities of the regulated lakes upstream are relatively small, however, and thus the human impact on the accumulated inflow of the forthcoming period is small, if studied in a monthly time step.

Secondly, the success of the model is studied in the two small basins, Ruunapuro and Heinäjoki, both of which are located upstream of Lake Päijänne. According to Kaitera (1939), the delay in the runoff in these kinds of small basins is very short because of the small basin area and the lack of lakes. Thus, long-term forecasting might turn out to be difficult. On the other hand, if the model can produce reliable forecasts for the small basins, the observations and the forecasts in these basins can be utilised in forecasting inflow to Lake Päijänne. The relation between similar small research basins and the large Seitakorva basin in Lapland has been examined by correlating their spring flow totals between May 1 and June 30 (Gürer, 1975). The results were not found to be satisfactory (maximum r=0.581). This was due to the differences in physical and hydrological characteristics of the basins.

Finally, the accuracy of the forecast model in Lake Pyhäjärvi is addressed. The lake is large compared with its basin and thus, lags are short. In addition, evaporation from the lake surface is a major factor in the water balance of the lake, especially during the summer months.

In the new approach, categorical long-term inflow and streamflow forecasts are generated. The approach is highly motivated by the current real-time operation policy of Lake Päijänne defined in the grant for the regulation license by the Eastern Finland Environmental Permit Authority (2002). The objective water levels of the forthcoming period are set based on the forecasts about the wetness of the forecast period. Five categories for the wetness are used. Earlier categorical long-term forecasts have been studied and applied by Simpson et al. (1993), Piechota et al. (1998) and Piechota and Dracup (1999). They approximated the occurrence probabilities of the different wetness categories (below normal, normal, above normal) of the forthcoming streamflow volumes in Australia and the United States by using climate indices.

The new forecast model is based on pattern recognition. Previously pattern recognition has been used both for the synthesis of streamflow data (e.g. Unny et al., 1981; Lall and Sharma, 1996; Prairie et. al., 2006) and for streamflow forecasting (e.g. Karlsson and Yakowitz, 1987; Yakowitz and Karlsson, 1987; Galeati, 1990; Shamseldin and O'Connor, 1996). Yakowitz and Karlsson used a NN rule to forecast one-day-ahead runoffs using the rainfall readings and runoff measurements of the past few days as features (Karlsson and Yakowitz, 1987; Yakowitz and Karlsson, 1987). The forecast was a weighted average of the runoffs of the nearest neighbours. The results were not significantly worse than the results of an ARMAX model that they used for comparison. A similar approach was used when Galeati (1990) forecast one-day-ahead discharges in a typical Alpine basin in the northeastern Alps by using the *k*-NNR. The results were as good as the ones of an ARX precipitation-runoff model but with a much simpler simulation structure. Shamseldin and O'Connor (1996) advanced the *k*-NNR for one-day ahead forecasting by adding a linear perturbation component to the model.

Smith (1991) used similar ideas in long-term forecasting. He presented the concept of using, for example, snowpack data as a feature in long-term forecasting but used only observed streamflow data in the implementation. Araghinejad et al. (2006) have used the *k*-NNR for long-term streamflow forecasting and the studies of Piechota et al. (1998) and Piechota and Dracup (1999) in long-term forecasting are based on the concepts of pattern recognition. The idea of trying to typify a forthcoming period based on meteorological or hydrological observations is not new in long-term forecasting. Already in 1938, Bydin stated that certain winter temperature patterns are connected with certain types of spring floods in River Svir (Bydin, 1938). A complete description of the new method follows in the next chapter. For an extensive review of the applications of pattern recognition on water resources management in general see Koskela (2004) and for the basic theories of pattern recognition, see, for example, Theodoridis and Koutroumbas (1999) or Schalkoff (1992).

3.1 Method

3.1.1 General methodology

The forecast model is based on supervised pattern recognition. Supervised pattern recognition is founded on a priori knowledge about the classes into one of which an unknown pattern should be classified. Normally this information is given in a form of a training set X that consists of patterns whose correct classes are known. In supervised learning, this information is used to build a classifier to categorise an unknown pattern into one of the classes. For streamflow forecasting the following method is used:

1. The training set is generated. All the years in the data set are classified into the different wetness categories based on the discharge sum distribution of the forecast period.
2. Feature vectors describing the hydrological state of the basin on a forecasting day are constructed for each year. A feature vector consists of a combination of the measurements on ground water levels, soil moisture, snow water equivalents, frost, discharges, precipitation, NAO indices and water levels. Weather forecasts are not used.
3. A supervised learning algorithm is used to classify a forthcoming period into one of the constructed wetness classes based on its feature vector.
4. The discharge forecast is calculated. The forecast is based on the discharge series of the years that belong to the class into which the new pattern was classified.

In principle, the approach chosen and the one used by Piechota et al. (1998) and Piechota and Dracup (1999) in categorical streamflow forecasting differ in two ways. Firstly, in step 3, Piechota et al. give the occurrence of streamflow in one of the categories in the form of probability. In the present study, it is only important whether the classification is correct or not. Secondly, Piechota et al. used features individually while approximating the occurrence probabilities of the forthcoming class and combined the results afterwards by using a linear combination of the probabilities. In this study, the feature vector consists of several variables simultaneously and features are equally weighted in classification.

Several algorithms are available in supervised pattern recognition. In this study, two algorithms are applied to classify new patterns into the constructed classes: the *k-nearest neighbour rule* and the *minimum distance classifier*. These classifiers were chosen because of their simplicity. Multi-parameter classifiers were not considered because of the restricted amount of data available. The Euclidean distance was used as a similarity measure in each of the case studies and all the data were standardized before the classification to avoid problems related to the different scales of the features.

The *k*-nearest neighbour rule (*k*-NNR) is popular and probably the best known of the nonlinear classification algorithms. This algorithm is strongly dependent on the training set X and thus the training set should be large and represent all the classes. When the *k*-NNR is used, an unknown pattern is classified into the class that has most of the *k* nearest neighbours of the new pattern. A simplified example is of course the nearest neighbour rule, in which an unknown pattern is classified into the class that contains the pattern that is most similar to the new object. Usually, an odd number is selected as k to avoid ties between the classes.

The algorithm can be presented as follows:

1) Choose the parameter k and the similarity measure.

2) Calculate the similarity between the new pattern and each of the patterns in the training set X.

3) Find the k patterns in the training set that were most similar to the new pattern and identify their classes.

4) Classify the new pattern into a class from which most of the k nearest training set patterns derived.

The limited amount of data sets an upper limit to the parameter value k. Three different values are tested: 1, 3 and 5. In a case of a tie, the new pattern is classified based on the nearest neighbour. It can be theoretically proven (e.g. Schalkoff, 1992) that the classification error probability of the NN classifier is at most twice as large as that of an optimal classifier for an infinite training set. Thus, the NN classifier is not optimal but often used, because it is practical and simple to execute.

The other classifier applied is based on *statistical pattern recognition*. By using the Bayes rule

$$P(\omega_i|\mathbf{x}) = \frac{p(\mathbf{x}|\omega_i)P(\omega_i)}{p(\mathbf{x})} \qquad \textbf{(3-1)}$$

the object $\boldsymbol{x}$ is classified into a class whose (posterior) probability $P(\omega_i|\boldsymbol{x})$ is largest. By assuming (a priori) equiprobable classes, with the same covariance matrices, the new pattern is classified into a class whose mean vector it resembles the most. This is a linear classifier called minimum distance classifier (MDC). Instead of comparing the new pattern with every object in the training set, the comparisons are made only between the mean of each class and the new pattern. The Euclidean distance is used as a similarity measure.

The real-time decisions about the operation of Lake Päijänne are based on the forecasts about the wetness category of the forthcoming inflow. However, to ease the release planning and to compare the accuracy of the model with other models, daily inflow forecasts and mean forecast of the accumulated inflow are needed. The mean forecast of the accumulated inflow is based on the inflow time-series of the training set. When a pattern is classified into a class ω_i, the daily inflow forecast f_t is calculated by using the average

$$f_t = \frac{1}{n}\sum_{j\in\omega_i} q_{j,t} \qquad \textbf{(3-2)}$$

where t stands for the date and j for the patterns (years) in the training set. In Equation 3-2, n is the number of the patterns in the class ω_i and $q_{j,t}$ is the observed daily inflow. As in the current study, for example Grantz et al. (2005) used the k-nearest neighbour rule for finding out the years from the historical records that remind the characteristics of the forecast year the most. Their final long-term forecasts were based, however, on the locally weighted polynomials of the streamflows of the nearest neighbours and thus the simplicity of the model was lost. As the final forecast is now based on each of the observations in the chosen class and weighting is not used, parameter calibration is not needed and the model remains simple.

As a consequence, however, the new method has two obvious weaknesses. Firstly, the forecasts of the accumulated streamflow given by the model never exceed the largest observation and are never lower than the driest observation. Therefore, the forecast errors concerning very wet and very dry years may be relatively large even if the forecast period has been classified correctly. Secondly, the theoretical confidence limits of the method are not estimated. The classification error probabilities are estimated, but their conversion into the confidence limits of the accumulated discharge is not straightforward. Empirical confidence limits based on the validation can be estimated, however.

3.1.2 Supervised classes

The accumulated inflow of Lake Päijänne for different periods beginning on April 1 is approximately normally distributed. An example of this attribute is given by showing the histogram of the accumulated inflow of the period between April 1 and September 30 in Figure 7. All observations of the period 1911-2006 (*n*=96) were used to constitute the histogram.

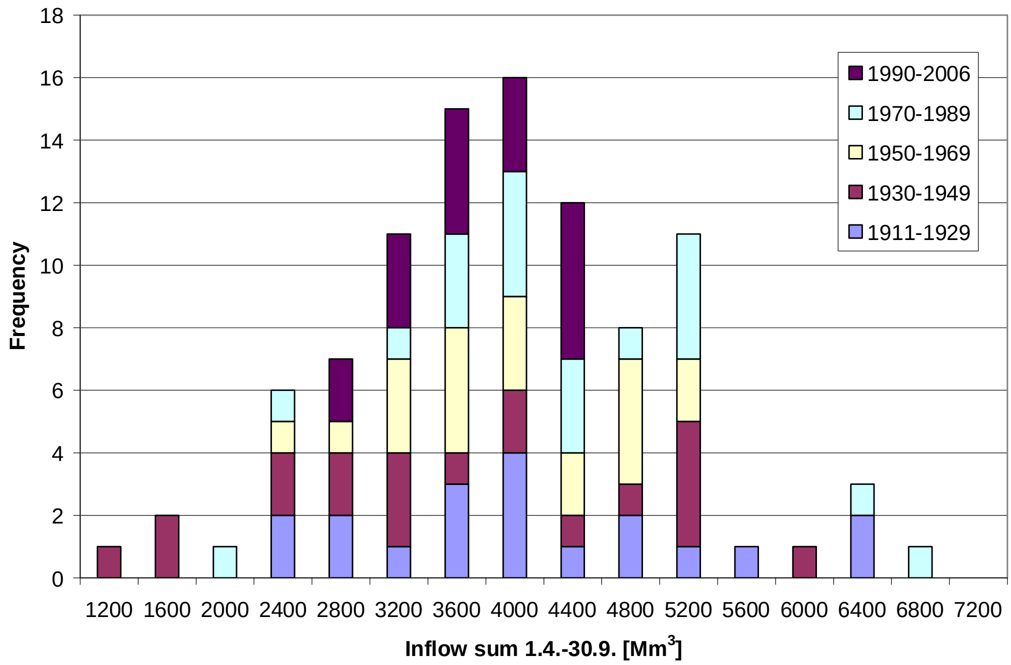


Figure 7. The histogram of the accumulated inflow of Lake Päijänne for the period between April 1 and September 30(1911-2006).

The estimated mean and the estimated standard deviation of the distribution for a time period of six months are 3944 Mm^3 and 1095 Mm^3. The normality of the sample was tested using the Jarque-Bera statistic:

$$JB = \left[\frac{N}{6}\right]\left[S^2 + \frac{(K-3)^2}{4}\right], \quad \textbf{(3-3)}$$

that follows a χ^2 distribution with two degrees of freedom. S is the skewness and K the kurtosis of the distribution. N is the number of observations. The Jarque-Bera statistic of the distribution was 0.63. It is less than the critical value 5.99 for the 95% test. Thus, the variable is, indeed, normally distributed. It is interesting and important to notice that the inflow sum distribution has not changed considerably during the century. Although not presented here, also the distributions of the accumulated inflows of the shorter periods beginning on April 1 for Lake Päijänne were estimated. The variables proved to be normally distributed, with different parameters, of course.

The accumulated inflows of the periods beginning on October 1 were not normally distributed, however. The density functions were right skewed and the kurtosis of the distributions were slightly over 0. In the Lake Pyhäjärvi study, the inflow sums of the periods beginning on April 1 were normally distributed except for the two longest periods. On October 1, the longest periods were normally distributed but the shortest were not. In Ruunapuro and Heinäjoki, the distributions of the streamflow sums were not normally distributed. The most suitable distributions for non-normally distributed variables were gamma distributions with different parameters.

Fitted distributions were used to form the supervised classes. The most obvious choice for separating different classes was used: the quantiles of the distributions of the accumulated inflow were selected as the thresholds. A study of the distributions corresponding to the periods with the non-normal behaviour showed only occasional differences in the classification of the periods if fitted normal distributions were used instead of the gamma distributions. Because the classification is based on the subjectively chosen quantiles in any case, fitted normal distributions were used for all case studies. The sensitivity of model accuracy for these choices is studied later. Three different combinations of the thresholds were tested. The data were divided either into three, four or five classes. When divided into three, a single year can be part of a “dry”, “normal” or “wet” class; when divided into four, part of a “very dry”, “dry”, “wet” or “very wet” class and when divided into five, part of a “very dry”, “dry”, “normal”, “wet” or “very wet” class. The classification of the periods into these classes was based on the quantiles of the fitted distributions.

In the case study of three classes, the 20% and 80% percentiles, in the case of 4 classes, the 15%, 50% and 85% percentiles and in the case of 5 classes, the 10%, 30%, 70% and 90% percentiles were used as thresholds. Thus the a priori probabilities in the classification of a new object are not equal. When using the minimum distance classifier, (a priori) equiprobable classes with the same covariance matrix are expected. The covariance matrices are unknown, but are assumed to be equal. By using the above thresholds, more observations are now categorised as “normal” than as “dry” and “wet” periods in the training set. By this decision, however, the accuracy of the inflow forecasts increases for the correctly classified wet and dry periods. On the other hand, for the correctly classified normal periods this causes a larger variance in the errors. Figure 8 gives some examples of the observed inflow sums of the period of six months in Lake Päijänne. The thresholds that divide the data into 5 classes are also shown.

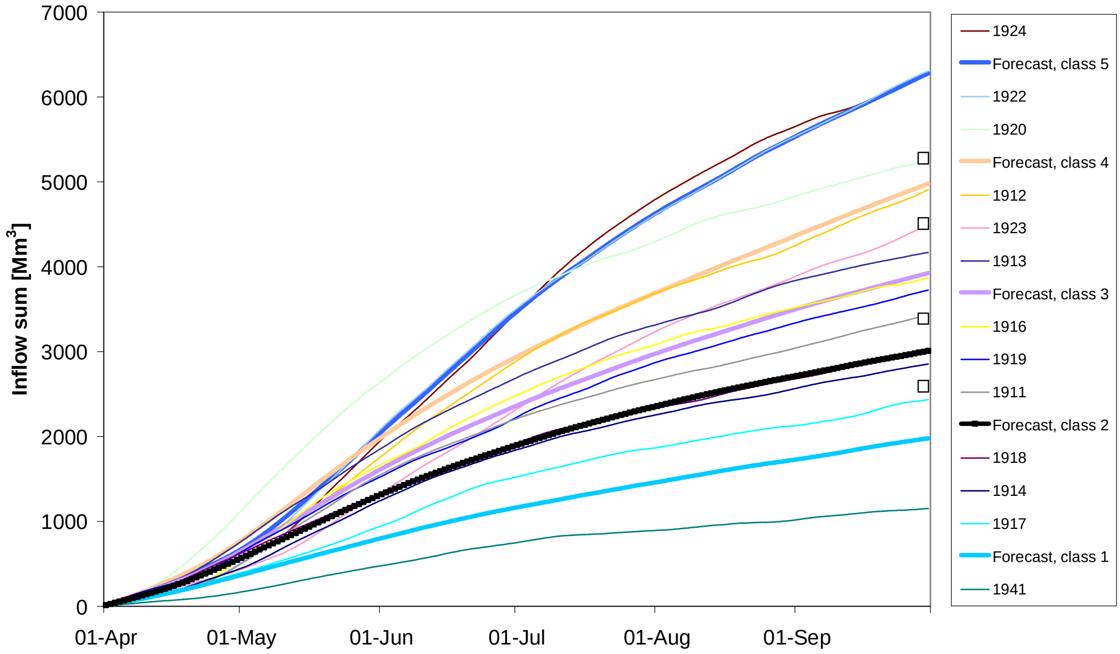


Figure 8. Some examples of the observed, accumulated inflow of Lake Päijänne and the percentiles that divide the observations into five classes (□). Also the forecasts for the different classes are presented.

Figure 8 presents also the inflow sum forecasts for each of the five classes for the forecast period of six months. As can be seen, the forecast of the accumulated inflow at the end of the forecast period varied between 1978 Mm^3 and 6278 Mm^3 depending on the class used. The chosen thresholds (percentiles) between the different classes and the forecasts of the accumulated inflow of each class (Equation 3-2) were not optimised in the sense of any goodness-of-fit test. It might be possible to decrease the theoretical error corresponding to a perfect classification by optimising these choices after the selection of a suitable goodness-of-fit test.

3.1.3 Representation of the classification results

The so-called confusion matrices are used in this thesis to present the results of the supervised pattern recognition application. The idea is simple and presented in Table 3. In an example, four classes into one of which an unknown pattern should be classified are used. Twenty-three patterns have been classified. Each cell describes the number of patterns n_{ij} classified into the class j (column) when it actually originates from the class i (row). Thus, the classification has been successful if a high percentage of the observations are on the diagonal of the confusion matrix. In the given example, 15 out of 23 patterns were classified correctly indicating a *classification error probability* (CEP) of 35% for the algorithm.

Table 3. An example of a confusion matrix.

Observed class\ Predicted class	*1*	*2*	*3*	*4*
1	**4**	2	1	0
2	0	**4**	2	1
3	0	2	**4**	2
4	0	0	0	**3**

3.1.4 Feature and model selection

When the number of the features used in the classification increases, so does the size of the problem in terms of the computational complexity. There is also no reason to use features that contain the same internal information about the differences between the classes. Generally, the greater the number of training set patterns compared with free classifier parameters, the better the generalization properties of the resulting classifier (Theodoridis and Koutroumbas, 1999). Thus, it is valuable to keep the number of features as small as possible. For the feature selection in a supervised pattern recognition problem, two main approaches can be used. It is possible to use statistical tests to approximate the difference between the average values of a chosen feature in different classes. If a clear difference is found, a feature is accepted. It is also possible to test the similarity between the feature vectors in different classes. If differences are not found, the test is repeated with another feature combination. The latter approach is used sequentially by a backward or forward feature selection algorithm to find the optimal features for the problem at hand.

It is also possible to decrease the dimension of the feature vectors to avoid problems related to similar features and high dimensions. Principal component analysis is one of the best known algorithms to achieve this goal (see e.g. Sharma, 1996). The dimension of the feature vector is decreased without losing any relevant information about the variability of the original features. The new variables are then used in the classification. One of the assumptions of the method is that each of the new variables describes some group of the original features.

In this work, some of the possible features were discarded based on a preliminary analysis for different reasons: a too short time-series, non-existent between class distances and a non-existent correlation with the accumulated inflows. After that, several models are calibrated, each with a different feature combination. Finally, the best models according to the chosen criterion in validation are discussed. This kind of method cannot be used if the selection has to be made between thousands or hundreds of possible features and models. For a small pool, however, the computational burden of calculating all the possible combinations with an unknown optimal number of features is not restrictive.

The criterion for selecting the best model is the estimated classification error probability. Thus, penalties are not calculated for the rank differences of the misclassified years. The criterion gives an equal value regardless of whether a wet period is misclassified into to the “normal” or “dry” class. Furthermore, the criterion does not take into account the number of observations used in validation. However, if several models give similar CEPs, the models with more observations used for validation and models with the lowest σ and the highest R^2 (see Chapter 3.1.5) are favoured. In addition, the cases of 3, 4 and 5 classes are studied separately.

3.1.5 Validation and comparison of the results

The evaluation of the models should rely strongly on the validation. The validation data should be chosen as large as possible, but at the same time the training set should be comprehensive and representative. Because of the restricted amount of data, the leave-one-out method (cross-validation) is used for the validation. The training set consists of N-1 observations and the validation is based on the excluded sample. By repeating this N times and excluding each time a different sample, the model is validated by using N samples. At the same time, all the problems related to the independence between the training and validation sets are avoided. In addition, the possible drawback of the holdout method, the representativeness of the small data sets, is avoided as well as possible.

Three performance factors are used to describe the success of the long-term inflow forecast model. Firstly, the estimated classification error probability (CEP) is calculated to study the performance of the pattern recognition algorithms. Secondly, the R-squared R^2 is used to study the performance of the inflow volume forecasts.

$$R^2 = 1 - \frac{\sum (F_i - Q_i)^2}{\sum (Q_i - \boldsymbol{Q})^2} \qquad \textbf{(3-4)}$$

where F_i is the forecast for the accumulated inflow and Q_i the observation. $\boldsymbol{Q}$ is the average of the observations. R^2 is sensitive to large absolute errors. Thirdly, the relative errors of the forecasts are calculated.

$$RE_i = \frac{F_i - Q_i}{Q_i} \qquad \textbf{(3-5)}$$

By studying the distribution of the relative forecast errors (mean μ and standard deviation σ) results can be later assessed in the light of the dependence between the accuracy of the model and the success of the regulation. As a goodness-of-fit measure, relative errors weight more the absolute accuracy of the dry periods (small values).

To compare the accuracy of the new method, also multiple linear regression models are used for forecasting. The regression models are estimated for each forecast site and forecast day. The leave-one-out method is used to evaluate the forecast accuracy of the linear models. Thus it is possible to compare the forecast accuracies of the methods by using the same data set.

3.2 Results for Lake Päijänne

3.2.1 The preliminary selection of the features

Nineteen possible features for describing the wetness of the forthcoming period on April 1 in Lake Päijänne and 17 features on October 1 were available. By using a preliminary study of all the possible features, a set of features was chosen. All the possible models, each with a different combination of features from this set, were tested and the results of the models with the best forecast power are finally shown. One of the goals of the preliminary study was to find as long time-series as possible to be able to validate the models properly. In Appendices B and C, the correlation matrices of the hydrological measurements and the accumulated inflow of the forthcoming period of a different length are presented. All the statistically significant correlations at 95% level are highlighted (bold). The number of pair-wise observations is not equal for all the pairs due to missing observations.

The water level of a regulated lake normally varies between fixed limits. The variations are partly independent of the hydrological state of the basin due to the unnatural release sequences. Thus, the use of the water levels of the regulated lakes as independent variables or as features should be carefully justified. Lake Pielavesi and Lake Konnevesi in the Rautalampi watercourse are unregulated and hence, the water levels of the lakes are fit for discharge forecasting downstream. The water levels of these lakes on the forecast dates are highly correlated with the forthcoming inflow volume of Lake Päijänne (r=0.45-0.89). Thus, they could be used as possible features on both dates. However, the lakes are located in the same sub-basin and their water levels are highly correlated with each other (r = 0.94 on April 1 and r = 0.90 on October 1). Thus only one of them should be used as a feature in the same application. The within class variances and the between class distances of these variables are similar. The class averages differ, but the within class variances are relatively large. The values of the neighbouring classes are overlapping. In April, the differences are slightly more explicit for Lake Pielavesi. The time-series of Lake Konnivesi is longer than the series of Lake Pielavesi, but both of the variables were chosen for the final set of features on both forecast dates. They are not used at the same time, however.

The regulation of Lake Keitele is conservative and follows the natural water level of the lake. On both forecast dates, the water level is highly correlated with the forthcoming inflow of Lake Päijänne. Correlation coefficients vary from r=0.30 between $Q_{Apr-Sep}$ and $W_{Keitele}$ on April 1 up to r=0.84 between Q_{Oct} and $W_{Keitele}$ on October 1. Although located in a different sub-basin, the water level is also highly correlated with the water levels of Lake Konnevesi and Lake Pielavesi (r=0.80-0.87). Especially for the longest forecast periods, there are clear differences in the average values of the water levels between different classes (“dry”, “normal”, “wet”), although the variances are large. Thus, the water level of Lake Keitele was chosen for the final set of features on both forecast dates.

Lake Kivijärvi, Lake Kiimasjärvi, Lake Saarijärvi, Lake Leppävesi and Lake Vesijärvi are regulated. The regulation rule for Lake Leppävesi has not been significantly changed since the beginning of the regulation in 1961 and therefore, the water level of the lake could be used as a feature, assuming that the regulation has been systematic from year to year. The state of the lake is, however, correlated with the water levels of the lakes upstream (Konnevesi and Keitele). In addition, the correlation of the water level on April 1 with the forthcoming inflows of Lake Päijänne is not as strong ($r \leq 0.59$). This is probably due to the small volume of the lake. In addition, the water level of the lake is highly correlated with another possible feature, the accumulated inflow of Lake Päijänne during a period preceding the forecast date. This is expected because the lake empties straight into Lake Päijänne. Especially in autumn, the class averages of this feature differ from each others, but the within class variances are also considerably large. The water level of Lake Leppävesi was not selected for the final set of the features.

The regulation rule for Lake Kivijärvi changed in 1957. The lake is located in the same sub-basin with Lake Keitele and on the chosen forecast dates, the water levels of the lakes are highly correlated (r=0.54 on April 1, r=0.82 on October 1). The water level of Lake Kivijärvi was not chosen for the final set of the features on April 1 but was tested in the final set on October 1. The reason was the high correlation (r=0.82) with the forthcoming inflow volumes of Lake Päijänne in late autumn. The class averages corresponding to the water level observations also differ more clearly on October 1 than on April 1.

The regulation rules of the two regulated small lakes in the Saarijärvi watercourse have been changed significantly during the years. The operation licence of Lake Saarijärvi changed in 1975 and the licence of Lake Kiimasjärvi in 1982. Because long stationary time-series were required in the application, the water levels of Saarijärvi and Kiimasjärvi were not utilised in forecasting. In addition, by studying the class averages and the within class variances of these variables, no reasons were found to use them as features. Taking into account the relative small volumes of these lakes, the loss of information due to this decision is not regarded significant. The water level of Lake Vesijärvi was not used as a feature either. The available time-series from the beginning of the regulation in 1975 is relatively short. In addition, the correlations between the water level of the lake and the inflow sums of the forthcoming periods in Lake Päijänne are not especially large (r=0.15-0.65).

Observations from six different groundwater level gauging stations were available. To validate the model properly, long time-series are needed. The groundwater time-series are only about 30 years long. In order to extend one of the groundwater time-series, a linear regression model was built. The goal was to achieve an extensive time-series for the period 1962-2003 to reliably test the usability of groundwater data in forecasting. Although only one of the time-series was extended, the suitability of the observations of each of the groundwater stations for long-term inflow forecasting was tested in the preliminary feature selection procedure. However, the use of these in the model would cause problems in the validation, because of the missing observations at the both ends of the time-series.

A natural candidate to be extended was the groundwater time-series (1976-2003) of the Äijälä station because of its location just upstream of Lake Päijänne (see Chapter 2.5.3 and Figure 1). To extend the time-series by using a linear regression model, either Pieksämäki or Padasjoki observations (1962-1994) should be used as an independent variable. Unfortunately, the linear regression model using the observations from the Äijälä station on April 1 as a dependent and the observations from these two stations on April 1 as independent variables was not statistically significant. Although the Pieksämäki station is not located in the Lake Päijänne basin, its observations (1962-1994) have a significant correlation with the forthcoming inflow volumes of a different length of Lake Päijänne on April 1. Thus, the next attempt was to extend the Pieksämäki time-series. The groundwater level in Mutkala on April 1 was used as an independent variable because these two stations are located on the same side of Lake Päijänne and in a similar soil area (moraine). The decision on which would be the independent variable was made based on the need for using the model for prediction. With the choice made, only 9 years (1995-2003) had to be predicted, instead of 14 years (1962-1975) with the other decision. The model was calibrated using the observations from 1976 to 1994, resulting in the formula

$$GW(1.4.)_{Pieksämäki} = 17110{,}8 - 1{,}69780 \cdot GW(1.4.)_{Mutkala} \qquad \textbf{(3-6)}$$

The slope in the model has a negative sign, because the Pieksämäki groundwater levels are given as a distance from the surface level, whereas Mutkala values are groundwater levels measured from the sea level. The constant term describes the difference between the base points.

Both model coefficients were clearly statistically significant with p-values of 0.000. In addition, the model itself was significant with F-test value 49.58 and p-value 0.000. The assumptions made on the model residuals were also tested. The residuals were summed up to zero indicating an unbiased model and the normality assumptions were accepted with the Wilk-Shapiro test value 0.9498. The autocorrelations of the residuals were insignificant and no severe heteroscedasticity in the residuals was found. Therefore, the model was accepted and used to extend the Pieksämäki groundwater time-series. The linear model, the calibration points and the predicted values that were used to extend the Pieksämäki groundwater time-series are presented in Figure 9.

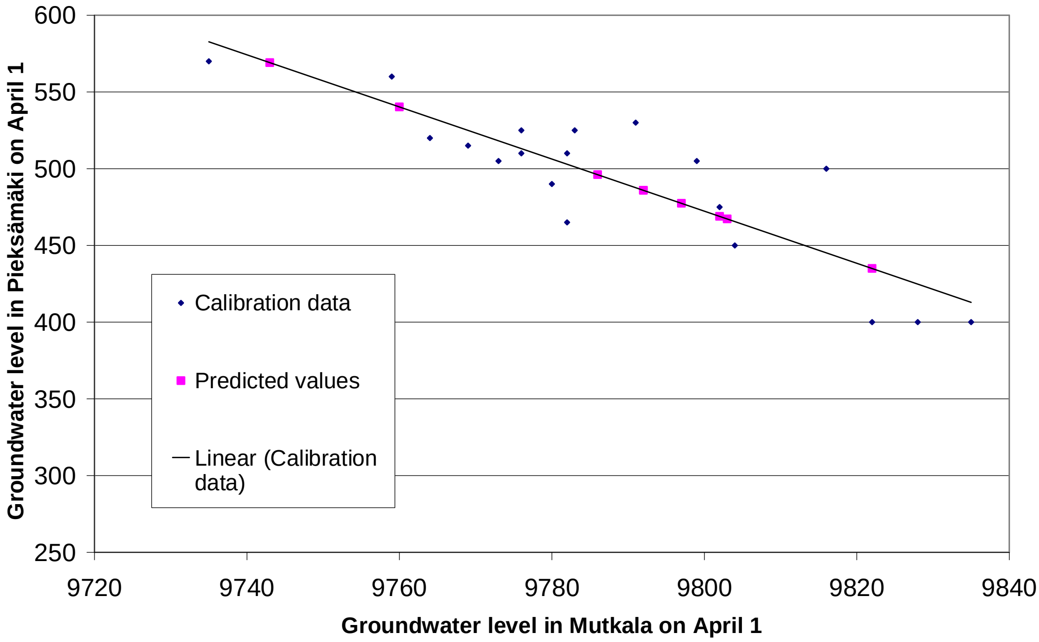


Figure 9. The linear regression model used to predict the groundwater level in Pieksämäki on April 1 for the years 1995-2003.

Also the correlations between the forthcoming inflow of Lake Päijänne and the states of the groundwater tables were calculated. The correlations decrease as the forecast period gets longer. These correlations are statistically significant only for the shortest periods. When the correlation matrix is analysed, it should be remembered that some of the Pieksämäki groundwater values are calculated by using the regression model.

This relation explains the highly significant correlation factor between the Pieksämäki and Mutkala observations. Consequently, only one of these observations should be used as a feature in the application. In any case, high multicollinearity restricts the use of the groundwater values. Significant correlations were also found between the water levels of the examined lakes and the groundwater levels. The observed and estimated groundwater levels in Pieksämäki were selected into the final set of possible features on April 1, because of the length of the time-series. For comparison, also the groundwater level observations from the Naakkima station were selected into the final set of possible features.

On October 1, the correlations between the groundwater levels and the inflow volumes of the forthcoming periods in Lake Päijänne are higher. They are significant also for the periods of 4-6 months. Despite the mutual correlation, both the groundwater level in Naakkima and Mutkala were selected for the final set of features. Also the groundwater observations in Vehkoo are tested in the final set by using it instead of the Naakkima observations. The correlations between the groundwater levels and the forthcoming inflow sums vary between 0.63 and 0.79 for Mutkala and Naakkima.

Both available areal snow observations correlate with the inflow sum (except for one month's period) in spring. A highly significant correlation (0.86) between the two variables was found, however. Therefore, only one of these values should be used as a feature. If one of the values is already in use in the algorithm, the other will not provide any new information. The areal snow water equivalent describing the areas near Lake Päijänne was used because of the higher correlation with the inflow and the longer time-series. Also the between class differences are clearer for this variable. Significant correlation coefficients were not found between the snow water equivalent and the other possible features.

The areal accumulated precipitation was calculated for different periods. The accumulated precipitation of the period between August to October (1.8.-31.10) was selected as a possible feature in forecasting of the inflow volumes during the next spring. This variable has a small correlation with the inflow volumes, but it also correlates with the groundwater observations and water levels of the upstream lakes on April 1. The within class variances are large but the averages are, however, unequal. The precipitation sum is one of the features in the final set in spring flood forecasting. For the forecast periods beginning on October 1, several possible precipitation sums were tested. The one with the highest correlation, the areal precipitation sum from May 1 until the end of September, was chosen as one of the features in the final set. The correlation between this sum and the Päijänne inflow volume from October 1 onwards varies between 0.75 and 0.86 for the different time periods. High correlation coefficients between the precipitation sum and the other features used (water level, groundwater level) were also found. Thus it is expected that it is not worthwhile to use all of the features in the final set at the same time.

The index describing the North Atlantic Oscillation during the December-February season correlates with the inflow sum of Lake Päijänne for April (r=0.38). For the forecast periods exceeding one month, the correlations are less significant (r<0.3). For the forecast periods starting on October 1, no linear connection between the inflow sum and the preceding NAO indices were found. The NAO indices were tested for forecasting on April 1 but not on October 1.

The inflow volume of the period preceding the forecast date was one of the features in the final set. On both forecast dates, the past and forthcoming inflow volumes correlate significantly. A two-week period was used, but an equally significant correlation coefficient for a period of four weeks was found. On both dates, differences in the class averages between the classes were found, although the tails of the distributions overlapped.

To sum up, all the models each containing a different combination of the following seven (eight) features are calibrated and validated to find the best model for inflow forecasting on April 1: the areal snow water equivalent in the areas near Lake Päijänne ($ASWE_{Päijänne}$), the state of the groundwater table in Pieksämäki ($GW_{Pieksämäki}$), the water level of Lake Konnevesi ($W_{Konnevesi}$) or Lake Pielavesi ($W_{Pielavesi}$), the water level of Lake Keitele ($W_{Keitele}$), the inflow sum of the period of a length of two weeks preceding the forecast date ($\sum Q2_{Päijänne}$) and the index of the North Atlantic oscillation during the December-February season ($NAO_{Dec\text{-}Feb}$). Both the Naakkima groundwater level ($GW_{Naakkima}$) and the areal precipitation sum during the preceding autumn ($\sum P_{Aug\text{-}Oct}$) were tested as the seventh variable.

In the case of forecasting the forthcoming inflow volume on October 1, the models using combinations of the following features are tested: the inflow volume of the period of a length of two weeks preceding the forecast date ($\sum Q2_{Päijänne}$), the areal precipitation sum during May 1-September 30 in the Päijänne basin ($\sum P_{May\text{-}Sep}$), the water level of Lake Konnevesi ($W_{Konnevesi}$) or Lake Pielavesi ($W_{Pielavesi}$), the water levels of Lake Keitele ($W_{Keitele}$) and Lake Kivijärvi ($W_{Kivijärvi}$), and the states of the groundwater levels in Naakkima ($GW_{Naakkima}$) and Mutkala ($GW_{Mutkala}$).

3.2.2 Forecasts on April 1

The leave-one-out algorithm was used to validate the success of the method for each of the feature combinations and classification algorithms. New objects were classified either by using the minimum distance classifier or the *k*-NNR with different values of the parameter *k*. In addition to the estimated classification error probabilities, the relative errors and the R^2 of the inflow volume forecasts were calculated. For details about the algorithms and validation, see Chapter 3.1. The results of the best models are collected into Table 7 (page 64). A more thorough analysis of the forecasts follows.

Forecast lead time: 1 month

For the forecasts of a time period of one month (Apr 1-Apr 30), several models gave practically equal results. None of the feature combinations outran the others. For three supervised classes, the model using MDC and a combination of the $ASWE_{Päijänne}$, the $GW_{Pieksämäki}$, the $W_{Konnevesi}$, the $\sum Q2_{Päijänne}$ and the $NAO_{Dec\text{-}Feb}$ as features gives a low estimated CEP (24%). The standard deviation of the relative forecast error (σ) was 19%, the mean of the relative errors (μ) +6% and the R-squared R^2=0.61. The confusion matrix is shown in Table 4. The wet periods are classified very well. Most of the problems are related to misclassifying the normal periods.

Table 4. The confusion matrix of the forecasts for a lead-time of one month in Lake Päijänne on April 1 by using $ASWE_{Päijänne}$, $GW_{Pieksämäki}$, $W_{Konnevesi}$, $\sum Q2_{Päijänne}$ and $NAO_{Dec\text{-}Feb}$ as features, the minimum distance classifier and three classes (n=41).

	1	*2*	*3*
1	**4**	1	0
2	2	**14**	5
3	0	2	**13**

In the case of five classes, one of the lowest CEPs was attained by using the model where the $GW_{Pieksämäki}$, the $W_{Konnevesi}$ and the $\sum Q2_{Päijänne}$ were used as features and the MDC for classification (Table 5). The estimated CEP increased compared with the case of three classes, and it was 44% (n=41). By using five instead of three classes, the inflow volume forecasts of the correctly classified periods are more accurate and therefore, the standard deviation of the relative forecast error does not increase (σ=19 %). R^2 was 0.53. Although the CEP is quite large, it is noteworthy that none of the “dry” and “very dry” years is misclassified into the “wet” and “very wet” classes and vice versa. Six examples of the final inflow forecasts are presented in Figure 10. In the upper row, some successful forecasts are shown. The forecast are based on the correct classification. The forecasts shown in the lower row are based on misclassification. The errors at the end of the period are large especially in 1993 and 1984. In 1993, the period turned out to be much drier than expected and in 1984, much wetter than expected.

Table 5. The confusion matrix of the forecasts for a lead-time of one month in Lake Päijänne on April 1 by using $GW_{Pieksämäki}$, $W_{Konnevesi}$ and $\sum Q2_{Päijänne}$ as features, the minimum distance classifier and five classes (n=41).

	1	*2*	*3*	*4*	*5*
1	**3**	0	0	0	0
2	1	**3**	1	0	0
3	0	4	**10**	2	1
4	0	0	3	**3**	2
5	0	0	1	3	**4**

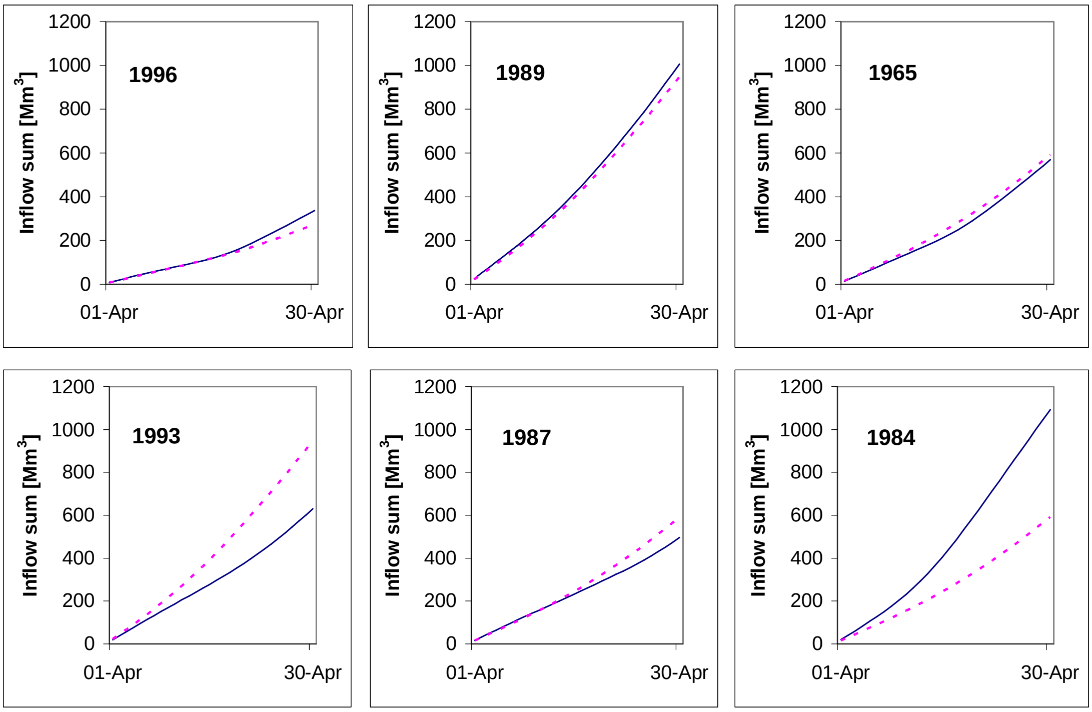


Figure 10. Six examples of the inflow forecasts for a lead-time of one month in Lake Päijänne on April 1. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

By using the *k*-NNR, the results are similar. The best results are obtained while using *k*=5. In the case of three supervised classes, several models with different feature combinations give CEPs that are close to 20%. In the case of five classes, the CEPs are normally around 50%. To demonstrate the forecast power of a model using only a single feature, the confusion matrix of the classification using $W_{Konnevesi}$ as a feature is shown in Table 6. The *5*-NNR was used for classification. The estimated classification error probability was 40%, the standard deviation of the forecast error 30% and R^2=0.39. The mean error μ was + 6%. Because of the long time-series of water level of Lake Konnevesi, it was possible to validate the model by using 96 observations.

Table 6. The confusion matrix of the forecasts for a lead-time of one month in Lake Päijänne on April 1 by using the *5*-NNR and five classes (*n*=96). A single feature, $W_{Konnevesi}$ was used.

	1	*2*	*3*	*4*	*5*
1	**2**	4	1	0	0
2	0	**13**	7	1	0
3	0	7	**29**	5	1
4	0	2	4	**8**	0
5	0	0	4	2	**5**

To compare the accuracy of the new model type, the same data set was used to estimate a multiple regression model for the inflow volume of Lake Päijänne in April. By using the whole data set and the backward elimination procedure in the variable screening, the $ASWE_{Päijänne}$ and the $\Sigma Q2_{Päijänne}$ were selected as independent variables. The estimated model is presented in Equation 3-7.

$$Q_{Apr} = 17.0917 \cdot ASWE_{Päijänne} + 2.11252 \cdot \sum Q2_{Päijänne} \qquad \textbf{(3-7)}$$

The model and the regression coefficients are statistically significant at 95% confidence level. The centered R-squared of the model is R^2=0.66 and σ=17% (μ=+2%, n=56). However, to compare the accuracy of the models fairly, also the forecast power of the linear regression model must be studied by using the leave-one-out method. By doing that, the R^2 of the model was 0.62 and σ=18% (μ=+3%, n=56). The results of the estimated multiple linear regression models are collected into Table 8 (page 64).

Forecast lead time: 2 months

The best models for forecasting the inflows of a time period of two months (Apr 1-May 31) are unbiased and the standard deviations of the relative forecast errors are slightly less than 20%. To reach this accuracy, it is possible to use both of the algorithms, different numbers of classes and different combinations of the features. When using 5 classes, the model using MDC and the $ASWE_{Päijänne}$, the $GW_{Pieksämäki}$, the $GW_{Naakkima}$ and the $W_{Keitele}$ as features gives the best results. The classification error probability is 32%, the standard deviation of the relative forecast error 18% and R^2=0.64. The mean relative forecast error is -5%. The confusion matrix, the forecast and the observed inflow volumes are presented in Figure 11. Also the theoretical forecasts based on the correct classification of the periods are presented. In the case of perfect classification, the standard deviation of the relative forecast errors (n=28) would have been 10%, showing the theoretical maximum accuracy of the method in the light of σ. A few examples of the forecasts for the case of five classes are also shown in Figure 12. Some forecasts based on the correct classification are presented in the upper row. In the lower row, forecasts are based on misclassification. In 1981 and 1991, the error at the end of the forecast period is large compared with the whole live capacity (1600 Mm^3) of the lake. Some problems can also be seen in the timing of the low and high flow periods in the correctly classified years (1984).

The model using three classes, 1-NNR and $GW_{Pieksämäki}$, the $W_{Konnevesi}$, the $\sum Q2_{Päijänne}$ and $\sum P_{Aug\text{-}Oct}$ as features gives a CEP as low as 11% (n=28). Although classification errors decrease compared with the use of four and five classes, the standard deviation of the errors is of the same order of magnitude, 18% (μ=+1%). Variance of the errors corresponding to the correctly classified periods is larger compared with models using more classes. The R^2 of the model using three classes was 0.50.

By using the backward elimination procedure, a multiple regression equation was estimated. $ASWE_{Päijänne}$, $\Sigma Q2_{Päijänne}$ and $W_{Konnevesi}$ were selected as independent variables and the model was forced through the origin resulting in an equation

$$Q_{Apr-May} = \beta_1 \cdot ASWE_{Päijänne} + \beta_2 \cdot \sum Q2_{Päijänne} + \beta_3 \cdot W_{Konnevesi} \qquad \textbf{(3-8)}$$

The forecast power of the model (Equation 3-8) was estimated by using the leave-one-out algorithm. The R^2 of the forecasts was R^2=0.55 and σ=17% (μ=+3%, n=55).

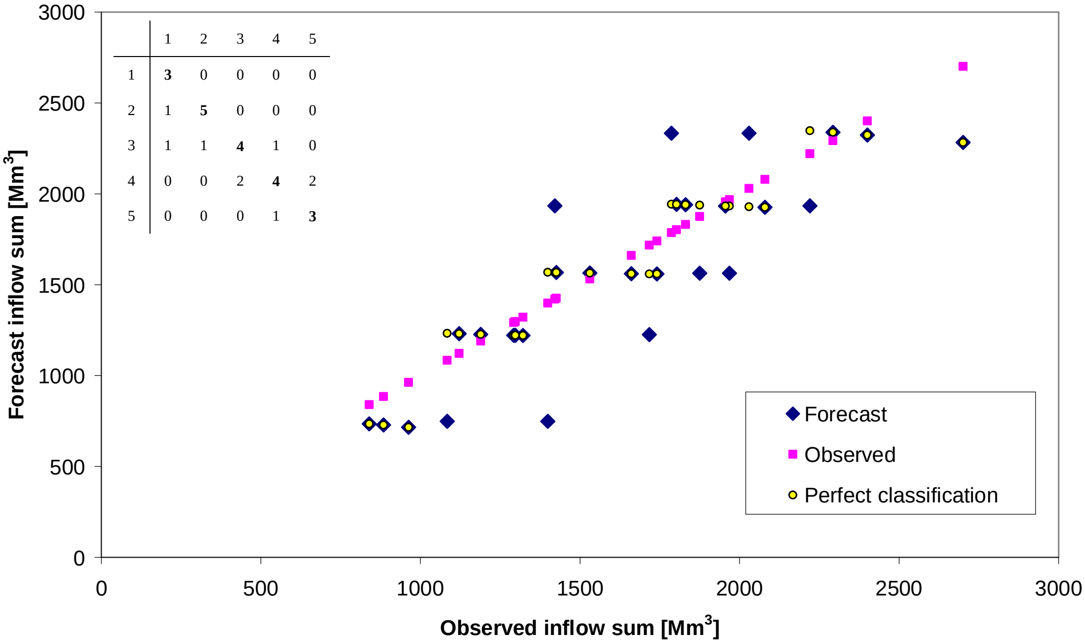


Figure 11. The confusion matrix, the observations and forecasts for a lead-time two months in Lake Päijänne on April 1 by using the MDC and 5 classes. $ASWE_{Päijänne}$, $GW_{Pieksämäki}$, $GW_{Naakkima}$ and $W_{Keitele}$ were used as features. Also the hypothetical forecasts based on the perfect classification are shown.

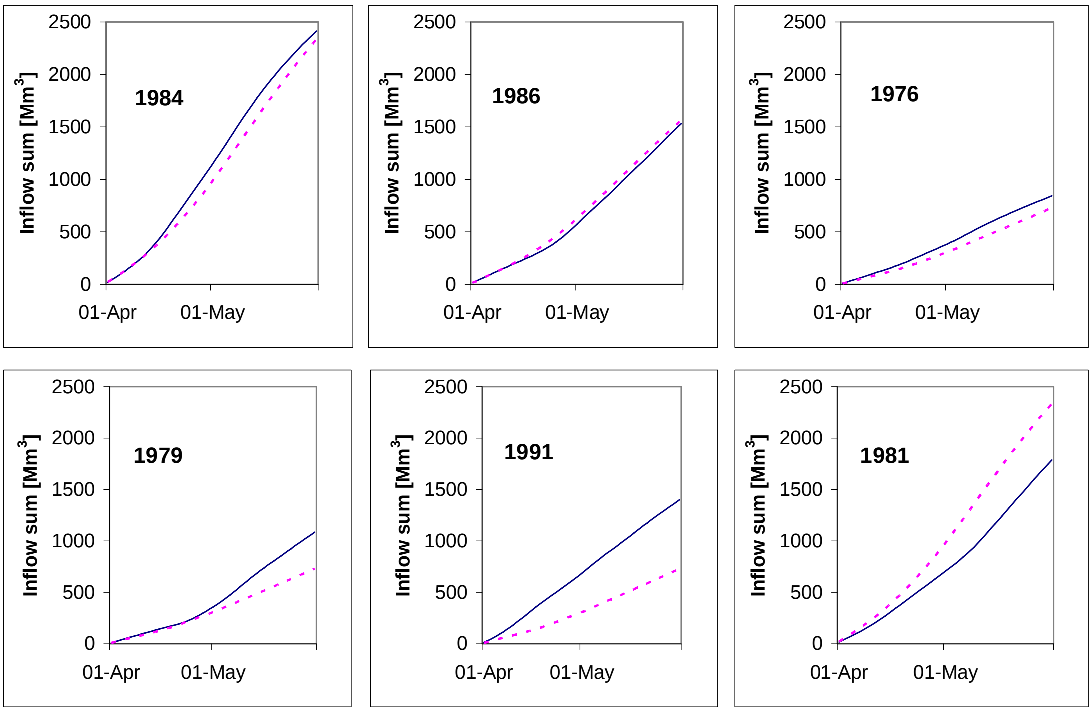


Figure 12. Six examples of the inflow forecasts for a lead-time of two months in Lake Päijänne on April 1. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

Forecast lead time: 3 months

The estimated classification error probabilities of the forecasts for a time period of three months (Apr 1-Jun 30) were similar to the forecasts for a time period of two months. The best σ were slightly lower, however. Combinations of $ASWE_{Päijänne}$, $GW_{Pieksämäki}$, $W_{Keitele}$ and $\sum Q2_{Päijänne}$ were used as features for the models with the best forecast power.

The lowest σ was attained while using four classes, the 5-NNR and the above mentioned variables as features. With the classification error probability of 26% (n=26), the standard deviation of the relative forecast error (σ) was only 15%. The R^2 was 0.61. The results are shown in Figure 13. In addition to the forecast errors due to the misclassifications, also the large forecast error corresponding to the wettest period is considerable, although this period was correctly classified. In general, the classification succeeded quite well.

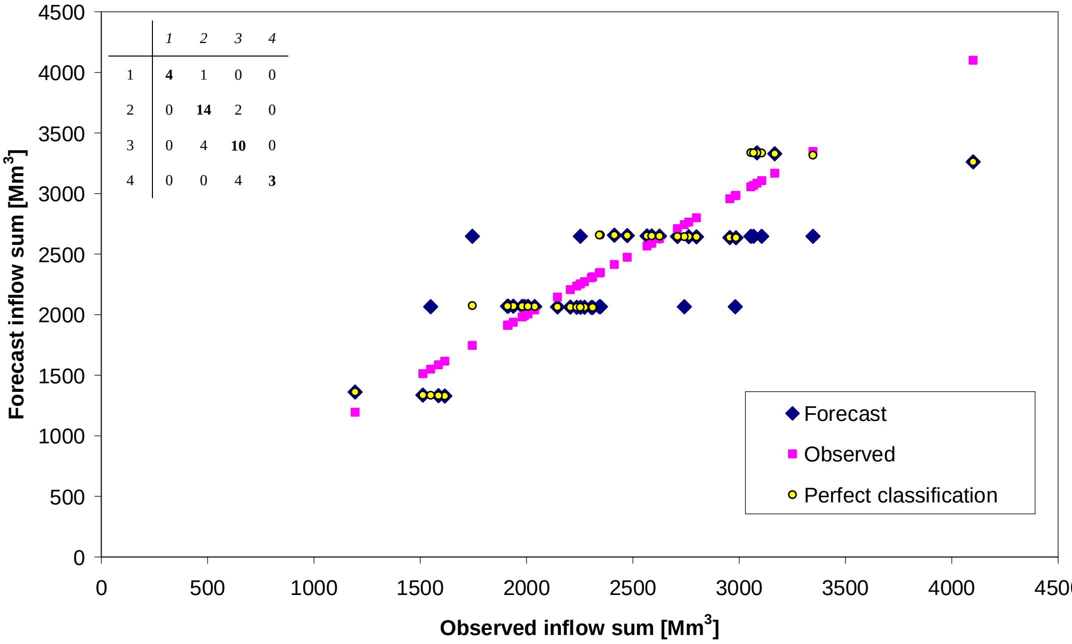


Figure 13. The confusion matrix, the observations and forecasts for a lead-time of three months in Lake Päijänne on April 1 by using the 5-NNR and 4 classes. $ASWE_{Päijänne}$, $GW_{Pieksämäki}$, $W_{Keitele}$ and $\sum Q2_{Päijänne}$ were used as features. Also the hypothetical forecasts based on the perfect classification are shown.

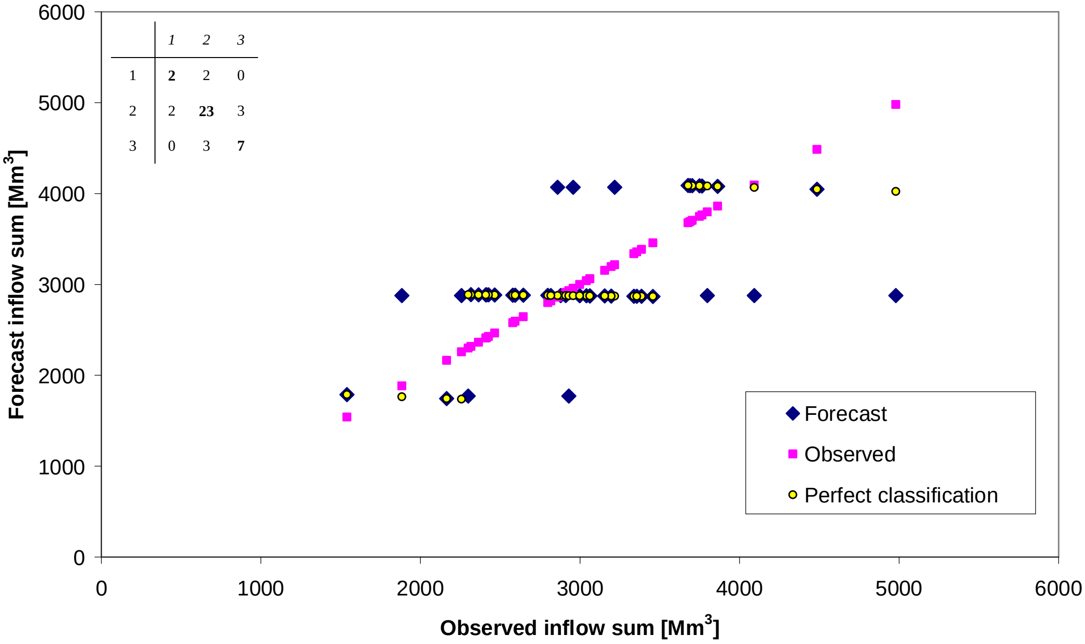
The same data set was used to estimate a multiple regression model for forecasting the inflow volume of the period between April 1 and June 30. By using the backward elimination, two variables were selected for the model: $ASWE_{Päijänne}$ and $\Sigma Q2_{Päijänne}$.

$$Q_{Apr-Jun} = \beta_0 + \beta_1 \cdot ASWE_{Päijänne} + \beta_2 \cdot \sum Q2_{Päijänne} \qquad \textbf{(3-9)}$$

By using the Equation 3-9 and the leave-one-out procedure, the R^2 of the forecasts was R^2=0.56 and σ=17% (μ=+2%, n=56).

Forecast lead time: 4 months

For the forecasts of a time period of four months (Apr 1-Jul 31), the areal snow water equivalent seems to be the most important feature. Otherwise the same features as for the shorter forecast periods in different combinations can be used to achieve satisfactory results. The accuracy of the best models is such that along with unbiased forecasts, the standard deviation of the relative forecast error is around 20%. By using three classes and $ASWE_{Päijänne}$ and $GW_{Pieksämäki}$ as the features, for example, and the *1*-NNR in the classification, the CEP is 24% (n=42) and σ=21%. At the same time, however, R^2 is as low as 0.12. The confusion matrix and the inflow sum forecasts based on this model are presented in Figure 14.



	1	2	3
1	**2**	2	0
2	2	**23**	3
3	0	3	**7**

Figure 14. The confusion matrix, the observations and forecasts for a lead-time of four months in Lake Päijänne on April 1 by using the *1*-NNR and 3 classes. $ASWE_{Päijänne}$ and $GW_{Pieksämäki}$ were used as features. Also the hypothetical forecasts based on the perfect classification are shown.

The same data set was used to estimate a multiple regression model for forecasting the inflow volume of Lake Päijänne of the period between April 1 and July 31. By using the backward elimination, the same independent variables were selected as in the case of forecasting the inflows for a time period of three months. Thus, the form of the equation is similar to Equation 3-9. The R^2 of the forecasts was R^2=0.56 and σ=16% (μ=+2%, n=56).

Forecast lead time: 5-6 months

For forecasting the inflows of a time period of five months (Apr 1-Aug 31) and six months (Apr 1-Sep 30), the best models are the ones using combinations of $ASWE_{Päijänne}$, $GW_{Pieksämäki}$, $W_{Pielavesi}$ and $\sum Q2_{Päijänne}$ as features. For some of the feature combinations, only a few observations were available for the "very wet" and the "very dry" classes. These extreme years seemed to concentrate on the periods where, for example, the groundwater observations were not available. Therefore, it was not possible to use the *3*-NNR and especially the *5*-NNR for some of the feature combinations. Compared with the shorter forecast periods it seemed, however, that the σ of the models was worse and the estimated CEPs grew in general. By using the four features already mentioned, some examples of the models giving as low σ as 20% was obtained. For example, the lowest estimated CEP for the forecasts of a time period of five months was achieved by the model using three classes, a single feature, $GW_{Pieksämäki}$, and the nearest neighbour rule. The CEP of the model was 14% and the standard deviation of the forecast error was 19% (Figure 15). It is important to notice that the lack of wet and dry years in the validation could overestimate the goodness of the model. The R-squared R^2 was 0.36 for these forecasts.

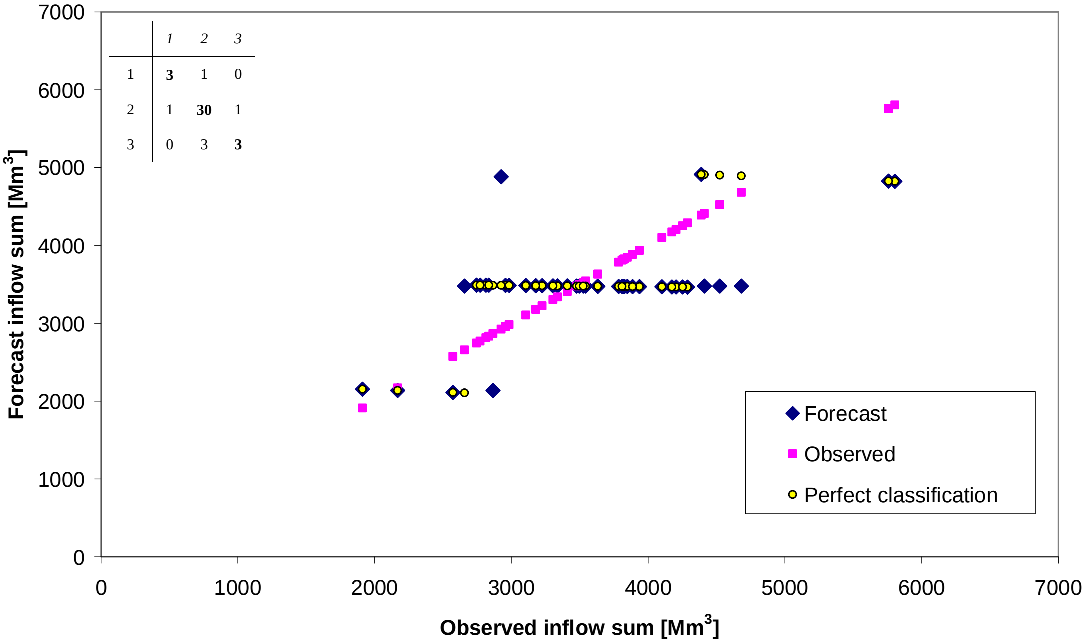


Figure 15. The confusion matrix, the observations and the forecasts for a lead-time of five months in Lake Päijänne on April 1 by using the *1*-NNR and 3 classes. $GW_{Pieksämäki}$, as an only feature, was used. Also the hypothetical forecasts based on the perfect classification are shown.

To demonstrate the accuracy of the forecasts of a time period of six months, a confusion matrix and inflow forecasts are presented for a model that uses $ASWE_{Päijänne}$ and $GW_{Pieksämäki}$ as features (Figure 16). While the CEP in the case of five supervised classes is 50% by using the *1*-NNR, the standard deviation of the relative forecast error was 20%. The R^2 was 0.26. In this case, the classification of the very wet and very dry years did not succeed. The number of observations of the classes in the training set was inadequate. Examples of the forecasts are shown in Figure 17. In the upper row, some of the forecasts that are based on the correct classification are shown. These forecasts are good, although some errors in the timing of the inflows are evident. The forecasts on the lower row are based on misclassification. In 1979 and 1988, the errors at the end of the forecast period are very large. The errors are only slightly less than the whole live capacity of Lake Päijänne.

The same data set was used to estimate multiple regression models for forecasting the inflow volume of both periods. The estimated models were similar to Equation 3-9. The R^2 of the forecasts was R^2=0.54 and σ=16% (μ=+2%) for $Q_{Apr-Aug}$ and R^2=0.49 and σ=17% (μ=+2%) for $Q_{Apr-Sep}$.

All the discussed results are collected into Table 7 and Table 8. As can be seen, for the new model type the lowest estimated CEPs were less than 15%, if only three supervised classes were used. The forecast models for the different lengths were practically unbiased and the standard deviations of the relative forecast error were slightly less than 20%, increasing only slightly or not at all as the forecast period lengthened. The highest R-squared R^2 was 0.64 and it decreased to around 0.25 for the longest forecast periods. For individual years, the forecast accuracy varied even from clear overestimation to underestimation as longer lead times were used. On the other hand, there were also examples where inflows are, for example, underestimated irrespective of the lead time. Examples of the forecasts for different lead times are shown for six years in Appendix F. Compared with the linear regression models, more variables and occasionally different variables were used for forecasting. In the light of R^2, the results of the multiple linear regression models were slightly better, especially for the longest forecast periods. This was true also in the light of σ, although the differences were small.

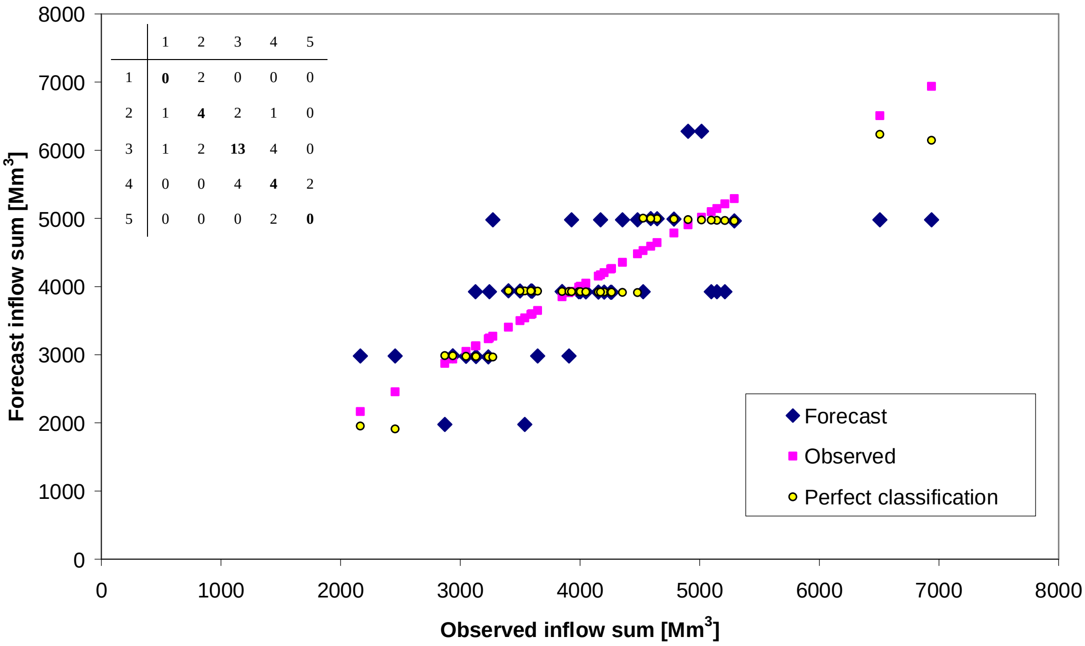


Figure 16. The confusion matrix, the observations and forecasts for a lead-time of six months in Lake Päijänne on April 1 by using the *1*-NNR and 5 classes. $ASWE_{Päijänne}$ and $GW_{Pieksämäki}$ were used as features. Also the hypothetical forecasts based on the perfect classification are shown.

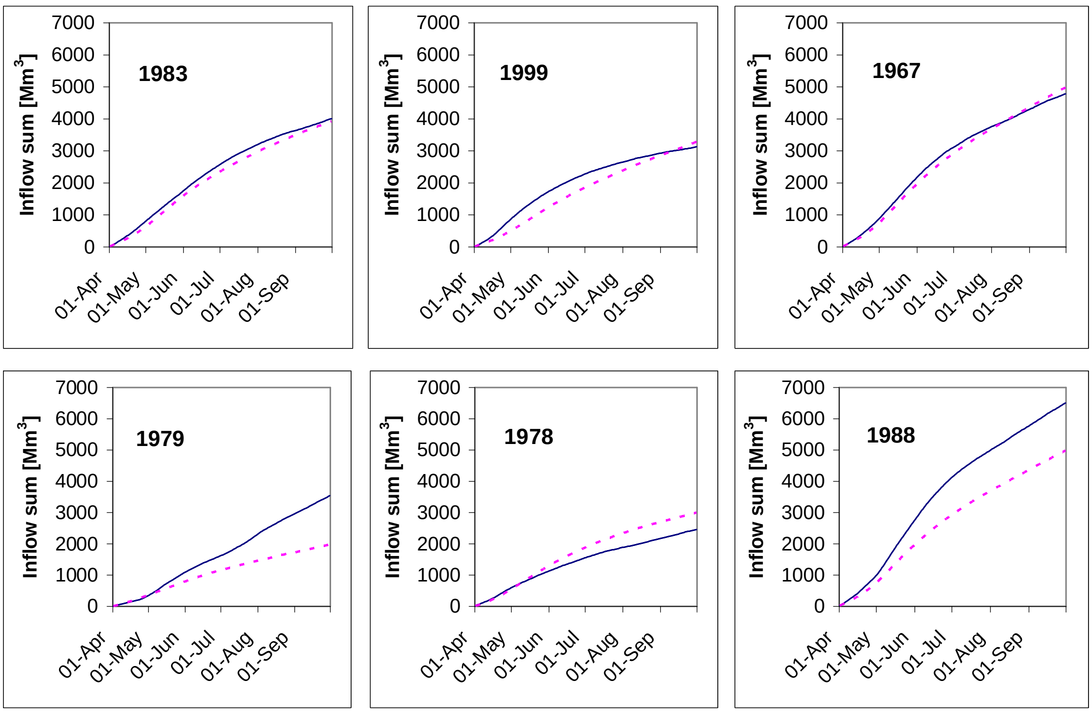


Figure 17. Six examples of the inflow forecasts for a lead-time of six months in Lake Päijänne on April 1. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

Table 7. The forecast accuracy of the new model type on April 1 in Lake Päijänne. The features used are marked with X.

Forecast length [d]	Number of classes	Pattern reg. algorithm	$ASWE_{Päijänne}$	$GW_{Pieksämäki}$	$W_{Konnevesi}$	$W_{Pielavesi}$	$W_{Keitele}$	$\Sigma Q2_{Päijänne}$	$GW_{Naakkima}$	$NAO_{Dec-Feb}$	$\Sigma P_{Aug-Oct}$	CEP [%]	R^2	μ [%]	σ	n
30	3	MDC	X	X	X			X		X		24	0.61	+6	19	41
30	5	MDC		X	X			X				44	0.53	- 3	19	41
30	5	5-NNR			X							40	0.39	+ 6	30	95
60	3	1-NNR		X	X			X			X	11	0.50	+1	18	28
60	4	3-NNR	X		X			X	X			32	0.60	0	15	28
60	5	MDC	X	X			X		X			32	0.64	-5	18	28
90	4	5-NNR	X	X			X	X				26	0.61	-3	15	42
90	3	3-NNR	X					X				20	0.51	+1	17	56
120	3	1-NNR	X	X								24	0.12	+3	21	42
120	4	1-NNR	X	X	X			X				32	0.33	+6	20	41
150	3	1-NNR		X								14	0.36	0	19	42
180	5	1-NNR	X	X								50	0.26	+1	20	42
180	3	1-NNR		X								19	0.23	0	22	42

Table 8. The forecast accuracy of the multiple regression models on April 1 in Lake Päijänne. The independent variables used are marked with X.

Forecast length [d]	Constant	$ASWE_{Päijänne}$	$GW_{Pieksämäki}$	$W_{Konnevesi}$	$W_{Pielavesi}$	$W_{Keitele}$	$\Sigma Q2_{Päijänne}$	$GW_{Naakkima}$	$NAO_{Dec-Feb}$	$\Sigma P_{Aug-Oct}$	R^2	μ [%]	σ	n
30		X					X				0.62	+3	18	56
60		X		X			X				0.55	+3	17	55
90	X	X					X				0.56	+2	17	56
120	X	X					X				0.56	+2	16	56
150	X	X					X				0.54	+2	16	56
180	X	X					X				0.49	+2	17	56

3.2.3 Forecasts on October 1

A drawback was present in the validation of the forecast models for the forecast periods starting from October 1. Most of the driest periods are concentrated on the first half of the 20^{th} century and most of the hydrological time-series are not available before the 1960s. Hence, none or only a single pattern was available for describing the driest classes in the case of four or five classes, if all the possible features were utilised. The thresholds dividing the supervised classes were not changed, however, and the validation of the model was based mainly on the success of the classification of the normal and wet periods. In Table 10 (page 71), the best results concerning the forecast accuracy of the models for the different forecast periods are presented.

Forecast lead time: 1 month

For the forecasts of a time period of one month (Oct 1-Oct 31), the lowest estimated classification error probability was achieved by using a model where $\sum Q2_{Päijänne}$, $\sum P_{May\text{-}Sep}$, $W_{Konnevesi}$, $W_{Kivijärvi}$ and $GW_{Naakkima}$ were used as the features and 5 classes with the *1*-NNR were used in classification. The CEP was only 11%, but only 26 years could be used to validate the model. The R^2 was as high as 0.86. However, very dry periods were not included in the validation. The standard deviation of the relative forecast error was 15%. In Figure 18 the confusion matrix and the inflow forecasts obtained by using this model are shown. As can be seen, observations from the “very dry” class were not available. The large errors in the inflow sum forecasts of the correctly classified very wet periods show the weakness of the method in forecasting extreme periods satisfactorily. The accuracy of the model would not have been much better, even if all years had been correctly classified. The forecasts of all the misclassified years are shown in the lower row in Figure 19. In the upper row, some of the forecasts that are based on the correct classification are presented. In 1981 the pattern is correctly classified, but inflows are still clearly underestimated. The error at the end of the forecast period is as large as are the errors corresponding to the misclassified years.

When using the *1*-NNR, three classes and $W_{Konnevesi}$ and $W_{Keitele}$ as features, the CEP of the model was 22%. This time, the model could be validated by using 50 years. The R^2 was 0.53 and σ was 17%. The confusion matrix is shown in Table 9. None of the wet periods is classified into the “dry” class and vice versa.

Table 9. Confusion matrix of the forecasts for a lead-time of one month in Lake Päijänne on October 1 by using three classes and *1*-NNR. $W_{Konnevesi}$ and $W_{Keitele}$ were used as features.

	1	*2*	*3*
1	**4**	4	0
2	4	**28**	1
3	0	2	**7**

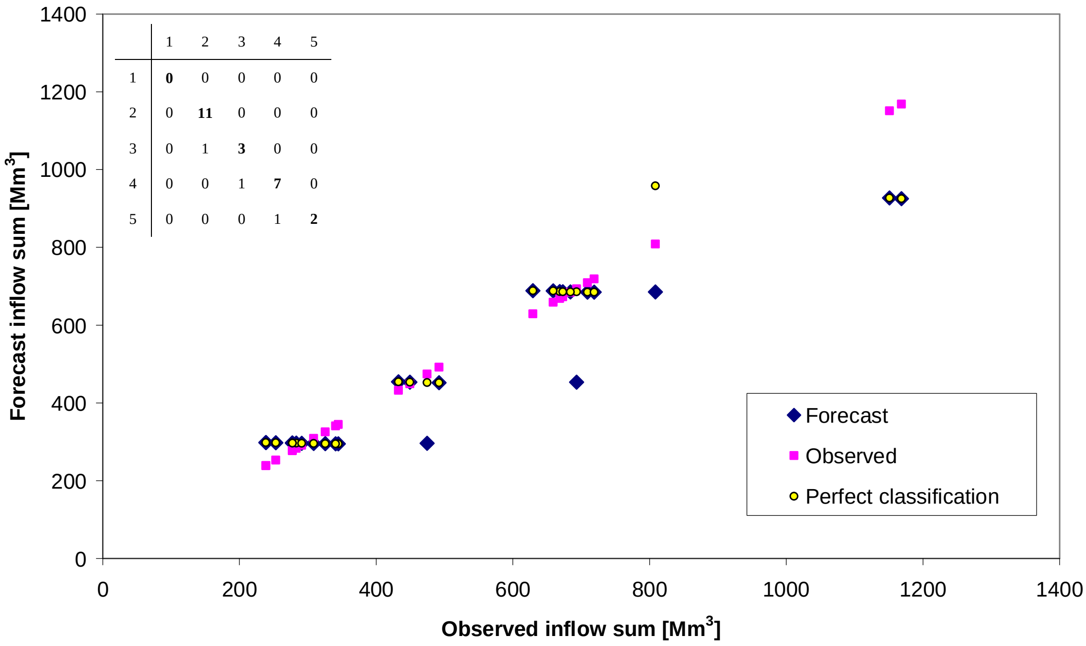


Figure 18. The confusion matrix, observations and forecasts for a lead-time of one month in Lake Päijänne on October 1 by using the *1*-NNR and 5 classes. $\sum Q2_{Päijänne}$, $\sum P_{May\text{-}Sep}$, $W_{Konnevesi}$, $W_{Kivijärvi}$ and $GW_{Naakkima}$ were used as features. Also the hypothetical forecasts based on the perfect classification are shown.

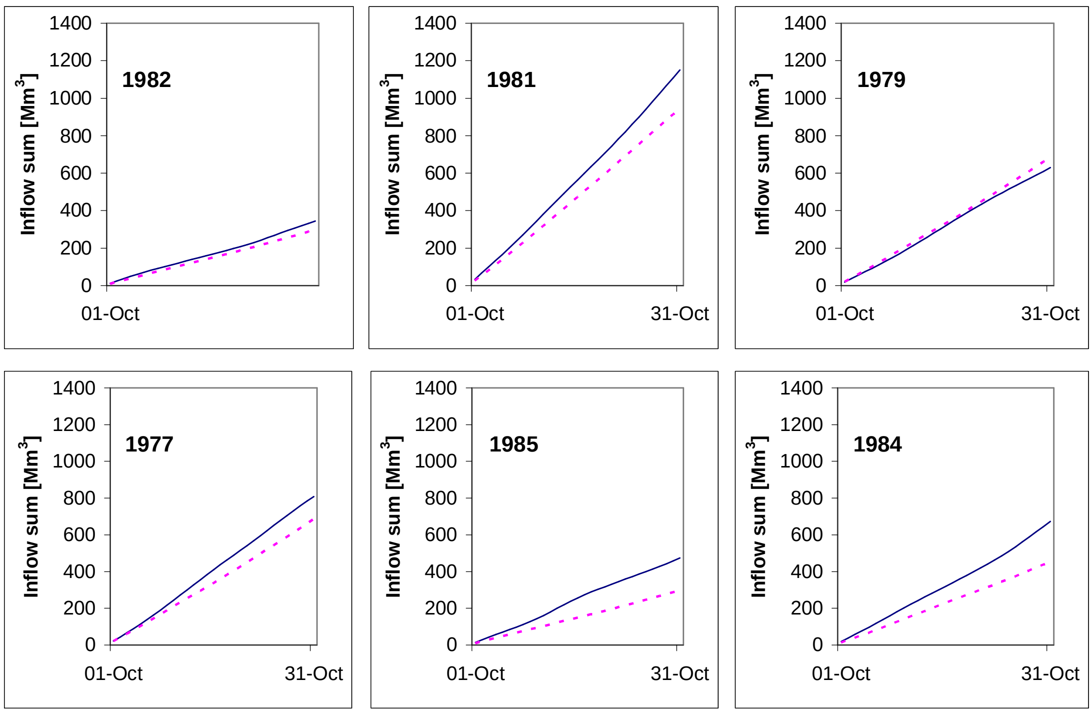


Figure 19. Six examples of the inflow forecasts for a lead-time of one month in Lake Päijänne on October 1. Darker line idicates the observation and lighter (dashed line) indicates the forecast.

For comparison, the same data was used to estimate a multiple linear regression model. By using the backward elimination, only a single variable was accepted into the model, $\sum Q2_{Päijänne}$, and the model was forced through the origin resulting in:

$$Q_{Oct} = \beta_1 \cdot \sum Q2_{Päijänne} \qquad \textbf{(3-10)}$$

The leave-one-out procedure was used to study the forecast power of the model. The R^2 of the forecasts was as high as R^2=0.88 and σ=21% (μ=+2%, n=96). Also the new model type was validated by using $\sum Q2_{Päijänne}$ as an only feature. Five supervised classes and MDC were used. The estimated CEP was 45%, σ=27% (μ=+0%, n=96) and R^2=0.70. Thus, the new model type does not utilise all the information given by the feature in the forecasts.

Forecast lead time: 2 months

Next the forecasts of a time period of two months (Oct 1-Nov 30) were studied. For the model using the combination of $\sum Q2_{Päijänne}$, $\sum P_{May\text{-}Sep}$, $W_{Konnevesi}$ and $W_{Kivijärvi}$ as features, five supervised classes and the minimum distance classifier, the estimated classification error probability was 27% (n=30) (Figure 20). The errors in the inflow forecasts are small (σ=19%, R^2=0.85), but the validation data do not contain any observations from the "very dry" class. The largest individual errors are related to the correctly classified very wet years. The lowest CEP, 17%, was obtained for the model using three classes and $\sum P_{May\text{-}Sep}$ and $W_{Konnevesi}$ as features (MDC). At the same time however, σ is as large as 30% and R^2 is only 0.60. Generally, the classification error probabilities of the models are larger compared with the models forecasting a time period of one month.

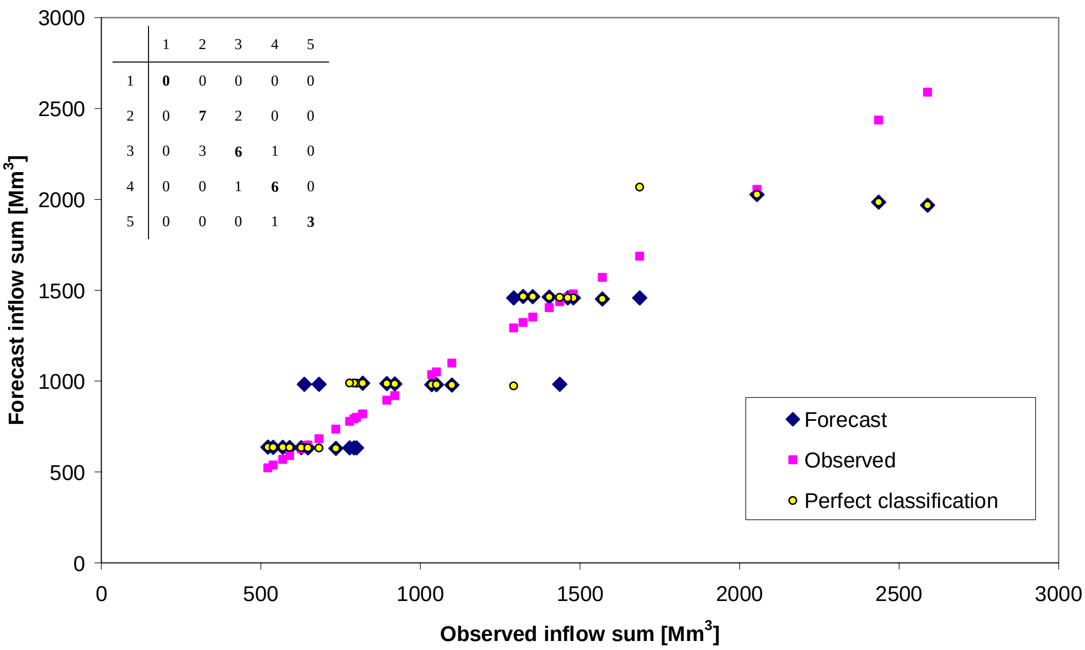


Figure 20. The confusion matrix, observations and forecasts for a lead-time of two months in Lake Päijänne on October 1 by using the MDC and 5 classes. $\sum Q2_{Päijänne}$, $\sum P_{May\text{-}Sep}$, $W_{Konnevesi}$ and $W_{Kivijärvi}$ were used as features. Also the hypothetical forecasts based on the perfect classification are shown.

The following model was estimated to compare the accuracy of the new approach

$$Q_{Oct-Nov} = \beta_0 + \beta_1 \cdot \sum Q2_{Päijänne} + \beta_2 \cdot W_{Pielavesi} \qquad \textbf{(3-11)}$$

The leave-one-out procedure was used for evaluating the forecast power of the model (Equation 3-11). The R^2 of the forecasts was 0.80 and σ=24% (μ=+6%, n=72).

Forecast lead time: 3 months

For the forecasts of a length of three months and longer, the best models use mainly combinations of $\sum Q2_{Päijänne}$, $\sum P_{May\text{-}Sep}$ and $W_{Konnevesi}$ (or $W_{Pielavesi}$) as features. The groundwater levels in the feature vectors do not give additional information on forecasting. In addition, the use of 4 and 5 classes instead of 3 is preferred because of the better overall results. In Figure 21 a confusion matrix and the inflow sum forecasts are given for the forecasts of a time period of three months (Oct 1-Dec 31). The feature vector of the model is simply a combination of $\sum P_{May\text{-}Sep}$ and $W_{Konnevesi}$. Five classes and the *1*-NNR were used. The lack of the very dry periods in the validation weakens the reliability of the result. The estimated CEP was 27% (n=30) and the standard deviation of the relative forecast error was 20%. The R^2 was as high as 0.85. Misclassifications are concentrated on the "normal" class. By using different combinations of the features and different numbers of the classes, the lowest estimated CEPs of the models varied normally between 20 and 35%.

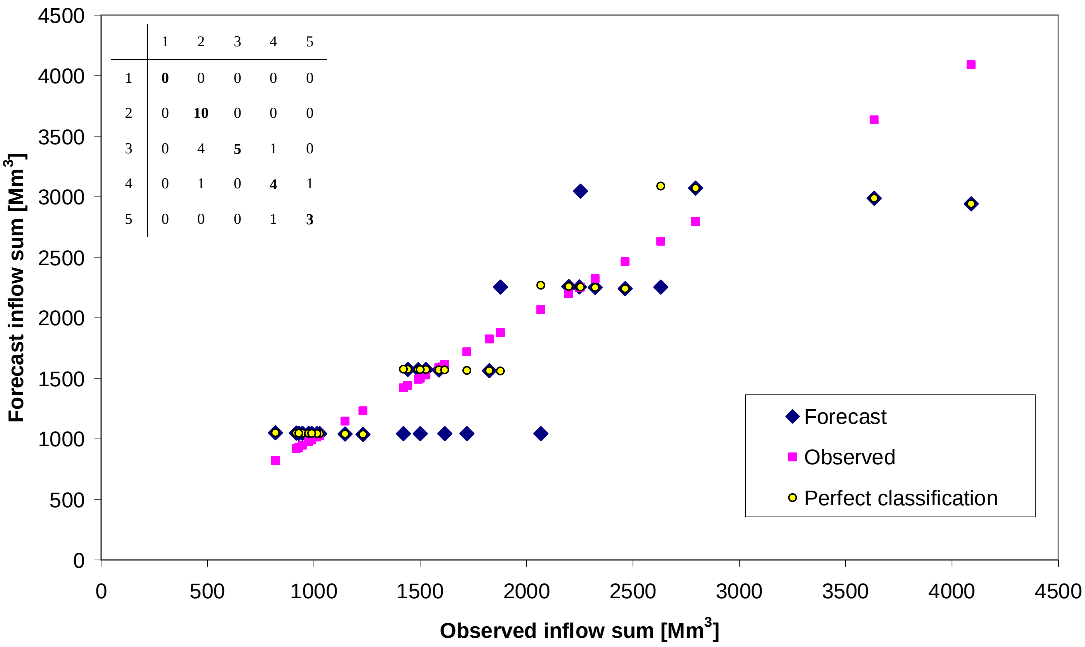


Figure 21. The confusion matrix and the observations and the forecasts for a lead-time of three months in Lake Päijänne on October 1 by using the *1*-NNR and 5 classes. $\sum P_{May\text{-}Sep}$ and $W_{Konnevesi}$ were used as features. Also the hypothetical forecasts based on perfect classification are shown.

A multiple linear regression model was again estimated for comparison. Same features were used as independent variables as in Equation 3-11. The leave-one-out procedure was used for evaluating the forecast power of the model. The R^2 of the forecasts was 0.70 and σ=26% (μ=+6%, n=72).

Forecast lead time: 4 months

For the forecast period of four months (Oct 1-Jan 31), the lowest estimated CEPs were naturally obtained by the models using three classes. The best accuracy of the inflow forecasts were obtained, however, by the models using five classes. An example of the results is given in Figure 22, where the confusion matrix and the inflow forecasts are presented for the best model. The *1*-NNR was used in the classification and $\sum P_{May\text{-}Sep}$ and $W_{Konnevesi}$ were used as features. The estimated CEP was 27% (n=30). The standard deviation of the forecast error was 19% and the R^2 was 0.70. Most of the problems in the classification are concentrated on the class "normal", although the largest errors are related to very wet years. The success of the model in the classification of the very dry years, however, could not be validated. By using the alternative classification algorithm, MDC and 5 classes, the results were similar. An equivalent linear regression model to Equation 3-11 was estimated for forecasting $Q_{Oct\text{-}Jan}$. The leave-one-out method was used to estimate the accuracy of the model. The R^2 of the forecasts was 0.65 and σ=25% (μ=+6%, n=72).

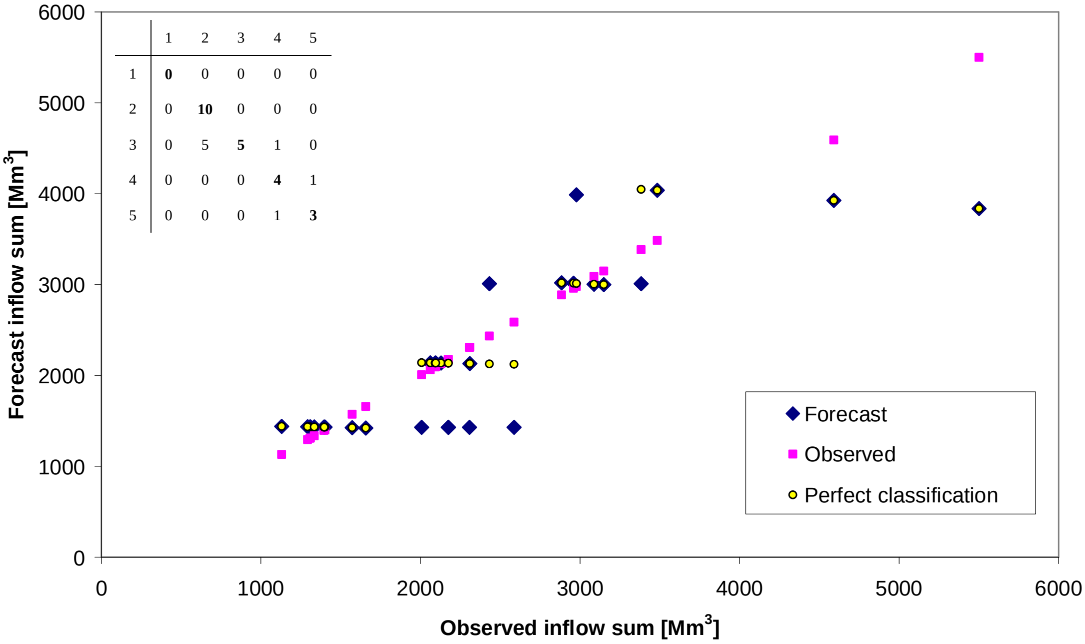


Figure 22. The confusion matrix and observations and the forecasts for a lead-time of four months in Lake Päijänne on October 1 by using the *1*-NNR and 5 classes. $\sum P_{May\text{-}Sep}$ and $W_{Konnevesi}$ were used as features. Also the hypothetical forecasts based on perfect classification are shown.

Forecast lead time: 5-6 months

For the forecast periods of five and six months, the results are similar to each other. Although the CEPs are slightly lower for the models using three classes, it is preferable to use more classes. Additional classes enable more accurate inflow forecasts for the correctly classified years. The CEPs do not seem to increase to such an extent that the additional accuracy would be lost. No single feature combination outran the others, but groundwater levels did not give additional information for the classification. For the forecast period of five months (Oct 1-Feb 28), the lowest CEP in the case of five supervised classes was 20% (σ=18%, R^2=0.72, n=30). This result was achieved by the model using $\sum P_{May\text{-}Sep}$ and $W_{Konnevesi}$ as features. Some examples of the forecast are shown in Figure 23. The forecasts in the upper row are based on correct classification and the relative forecast errors are less than 10% in these examples. In the lower row, forecasts are based on misclassification. In 1994 and 1984, the relative forecast errors at the end of the period are 35 and 41%, respectively. For the forecast period of six months (Oct 1-Mar 31), the CEP of the best model using five classes was 27% (MDC). $\sum Q2_{Päijänne}$, $\sum P_{May\text{-}Sep}$ and $W_{Konnevesi}$ were used as features. The standard deviation of the relative forecast errors was 19% (n=30) and R^2=0.70.

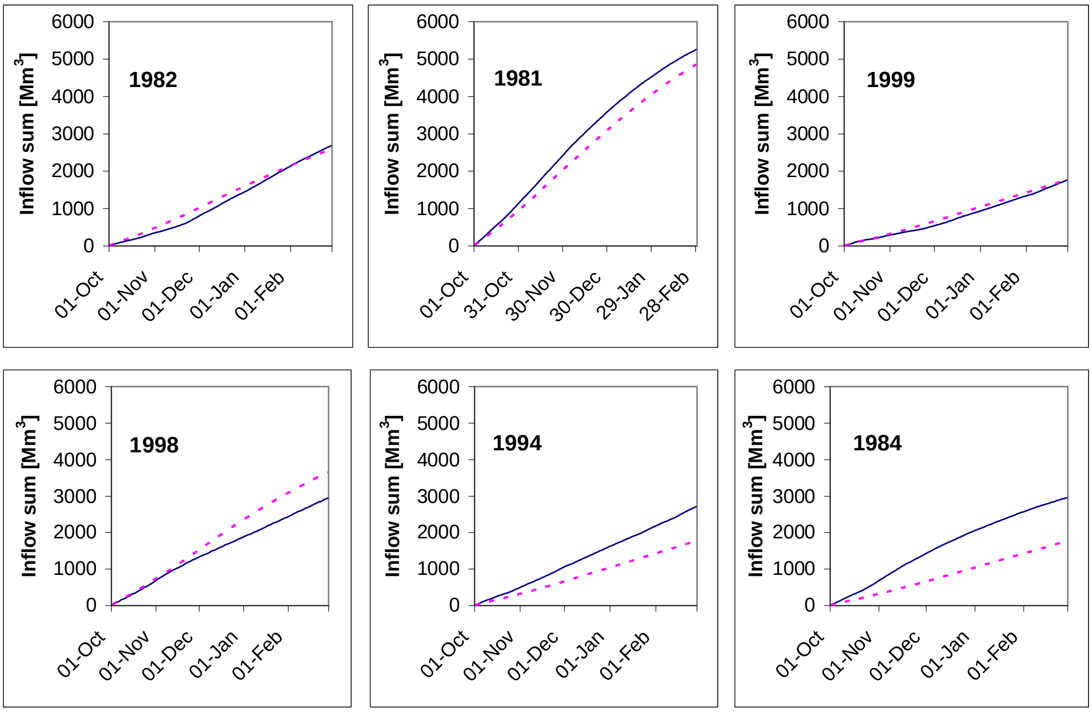


Figure 23. Six examples of the inflow forecasts for a lead-time of five months in Lake Päijänne on October 1. Darker line indicates the observation and lighter indicates the forecast.

Multiple linear regression models were estimated by using the same data set to compare the accuracy of the models. By using $\sum Q2_{Päijänne}$ and $W_{Pielavesi}$ as independent variables, the R^2 of the forecasts of $Q_{Oct\text{-}Feb}$ was R^2=0.61 and σ=25% (μ=+5%, n=72). The leave-one-out method was used for validation. Similarly by using the same independent variables for forecasting $Q_{Oct\text{-}Mar}$, the R^2 was 0.58 and σ=25% (μ=+4%, n=72).

All the discussed results are collected into Table 10 and Table 11. For the new model type, the CEP of the best model in the case of using three classes is as low as 11%. The R^2 varies from 0.86 to 0.72 being highest for the forecasts of a time period of one month. Compared with the linear regression models, R^2 is of the same order of magnitude, but more variables are used in forecasting. Thus, shorter time-series and fewer observations are used to validate the new model compared with the validation of the linear regression models.

Table 10. The forecast accuracy of the new model type on October 1 in Lake Päijänne. The features used are marked with X.

Forecast length [d]	Number of classes	Pattern reg. algorithm	$\Sigma Q2_{Päijänne}$	$\Sigma P_{May-Sep}$	$W_{Konnevesi}$	$W_{Pielavesi}$	$W_{Keitele}$	$W_{Kivijärvi}$	$GW_{Naakkima}$	$GW_{Mutkala}$	GW_{Vehkoo}	CEP [%]	R^2	μ [%]	σ	n
30	4	1-NNR	X	X				X		X		12	0.79	+2	24	26
30	5	1-NNR	X	X	X			X		X		15	0.85	0	17	26
30	3	1-NNR			X		X					22	0.53	+4	37	50
30	5	1-NNR	X	X	X			X	X			11	0.86	-3	15	26
60	5	MDC	X	X	X			X				27	0.85	+1	19	30
60	3	MDC		X	X							17	0.60	+3	30	30
60	5	3-NNR	X	X			X		X	X		27	0.85	-4	17	26
90	5	1-NNR		X	X							27	0.72	-4	20	30
90	5	MDC	X	X	X		X					30	0.80	0	19	30
120	5	1-NNR		X	X							27	0.70	-4	19	30
120	3	MDC	X		X		X	X	X	X		21	0.44	+6	34	28
150	5	1-NNR		X	X							20	0.72	-5	18	30
180	5	MDC	X	X	X							27	0.70	-2	19	30

Table 11. The forecast accuracy of the multiple regression models on October 1 in Lake Päijänne. The independent variables used are marked with X.

Forecast length [d]	Constant	$\Sigma Q2_{Päijänne}$	$\Sigma P_{May-Sep}$	$W_{Konnevesi}$	$W_{Pielavesi}$	$W_{Keitele}$	$W_{Kivijärvi}$	$GW_{Naakkima}$	$GW_{Mutkala}$	GW_{Vehkoo}	R^2	μ [%]	σ	n
30		X									0.88	+2	21	96
60	X	X			X						0.80	+6	24	72
90	X	X			X						0.70	+6	26	72
120	X	X			X						0.65	+6	25	72
150	X	X			X						0.61	+5	25	72
180	X	X			X						0.58	+4	25	72

3.3 Results for small basins

Long-term streamflow volumes were forecast for the two small streams, Ruunapuro and Heinäjoki on two dates. On April 1 a period of one to six months until the end of September and on October 1 until the end of March were forecast. The basis for the forecasts is the classification of the forthcoming period based on different features. In the case of the small basins, less than ten possible features were available. Thus, all the models, each containing a different feature combination, were assessed by comparing the results given by the leave-one-out method, and the models that have the best forecast power are discussed.

3.3.1 Ruunapuro basin, forecasts on April 1

In April, seven features describing the current hydrological state of the Ruunapuro basin are available for the classification: the areal snow water equivalent ($ASWE_{Ruunapuro}$), the frost depth in field (Fr_{field}), and forested sites (Fr_{forest}), the accumulated streamflow of a time period of two weeks preceding the forecast date ($\sum Q2_{Ruunapuro}$), the groundwater ($GW_{Äijälä}$) and soil moisture data in Äijälä ($SM_{Äijälä}$) and the accumulated precipitation ($\sum P_{Aug\text{-}Oct}$) in the basin. Based on the correlation analysis, the accumulated precipitation of the period between August 1 and October 31 in the preceding autumn is used as a possible feature. The correlations of this variable with the forthcoming streamflow volumes on April 1 are weak and insignificant at 95% significance level, however, for all of the forecast lengths. As expected, a significant correlation was found between winter precipitation and $ASWE_{Ruunapuro}$. From these two, the areal snow water equivalent is used as a feature. No connection between the NAO indices and the discharges in the small streams was found. Thus, the NAO indices are not used either.

The correlation matrix between the streamflow volumes of the forthcoming periods and the hydrological variables on April 1 is given in Appendix D. The correlation coefficients shown are based on different numbers of observations. The number varied from 12 to 49. The correlation coefficient describes the linear relationship between the variables. Thus the correlation analysis gives only an idea about features maybe usable in the application. Generally, the correlations are weak. The most significant correlations (r > 0.6) were found between $ASWE_{Ruunapuro}$ and the forthcoming streamflow volumes of a time period of three months and longer. For groundwater, discharge and precipitation, significant correlations with the forthcoming streamflow volumes were not found at all at 95% confidence level.

In advance, the success of the classification can also be predicted by calculating the within class and between class variability of the features. Differences were found between the average values of the available features in the different classes (“dry”, “normal”, “wet”), but the within class variances were large. Thus, it is expected that the classification success might be poor, at least if only a single feature is used.

The best models were selected based on the lowest estimated CEPs. In Table 12 results for different forecast lengths are shown. The lowest CEPs varied between 30 and 50% depending on the number of classes used in the application. In general the lowest estimated CEPs were obtained by the models using the combinations of $ASWE_{Ruunapuro}$, Fr_{field}, Fr_{forest} and $\sum Q2_{Ruunapuro}$ as features. If the standard deviation of the relative forecast error is studied, the best models gave σ as low as 21%. Except for the forecasts of a time period of one month, mean error μ is close to 0.

Table 12. The forecast accuracy of the new model type for Ruunapuro on April 1. The features used are marked with X.

Forecast length [d]	**Number of classes**	**Pattern reg. algorithm**	**$ASWE_{Ruunapuro}$**	**Fr_{forest}**	**Fr_{field}**	**$\Sigma Q2_{Ruunapuro}$**	**$GW_{Aijälä}$**	**$SM_{Aijälä}$**	**$\Sigma P_{Aug\text{-}Oct}$**	**CEP [%]**	**R^2**	**μ [%]**	**σ**	**n**
30	3	5-NNR	X			X				47	-0.60	+33	98	43
60	4	MDC	X	X	X					39	0.34	-4	22	36
90	3	MDC	X	X						33	0.25	0	24	36
120	4	MDC	X	X	X	X				39	0.39	-3	21	36
150	3	1-NNR	X			X				42	0.08	0	24	43
180	3	3-NNR	X			X				28	-0.05	+2	27	43

The weakest results are obtained for the forecasts of a time period of one month. For the small basins this is not a surprise. Depending on the forthcoming weather conditions, the timing of the snowmelt varies from year to year. Thus the successful classification of the forthcoming period without the weather forecasts turned out to be difficult. Those hydrological variables that foresee a wet spring do not necessarily affect the wetness of the first 30 days. This is especially true for $ASWE_{Ruunapuro}$. The correlation between Q_{Apr} and $ASWE_{Ruunapuro}$ on April 1 was only r=0.15 (see Appendix D).

Differences in the forecast accuracy of the models forecasting inflows of periods exceeding a month are small. For these periods, the lowest estimated CEPs vary between 28 and 42%. At the same time, σ varies between 21 and 27%. The R^2 is highest for the forecasts of a time period from two to four months (R^2=0.34; R^2=0.25; R^2=0.39). In the light of the estimated CEP and σ, the errors do not seem to increase as the forecast period lengthens. However, the R^2 is worse for the models forecasting a time period of five and six months. Although the estimated CEPs of the models are generally quite large, very poor classifications are rare. A period classified into a wet class rarely turns out to be a dry period and vice versa.

Six examples of the streamflow forecasts of a time period of four months are shown in Figure 24. The minimum distance classifier and four classes were used and $ASWE_{Ruunapuro}$, Fr_{field}, Fr_{forest} and $\sum Q2_{Ruunapuro}$ were used as features. Three examples in the upper row are examples of the forecasts based on correct classification. Forecast examples in the lower row are based on misclassification. In 1996, the hydrological state of the basin on April 1 is typical for a dry year. However, the avoidance of overestimating the forthcoming discharge sum is based on the wet period around the beginning of July. It is not really possible to foresee such phenomena by the model. In 1987, spring runoffs are nicely forecast, but a wet June causes a misclassification. In 1966, a very wet season was expected, but the period turned out to be wet. In 1994, the forecast is poor from the beginning. Spring runoffs are larger than expected. In the data set, deep frost is normally connected to low flows during the forecast period. In 1994, the opposite happened and thus the model that used both of the frost variables as features misclassified the forthcoming period.

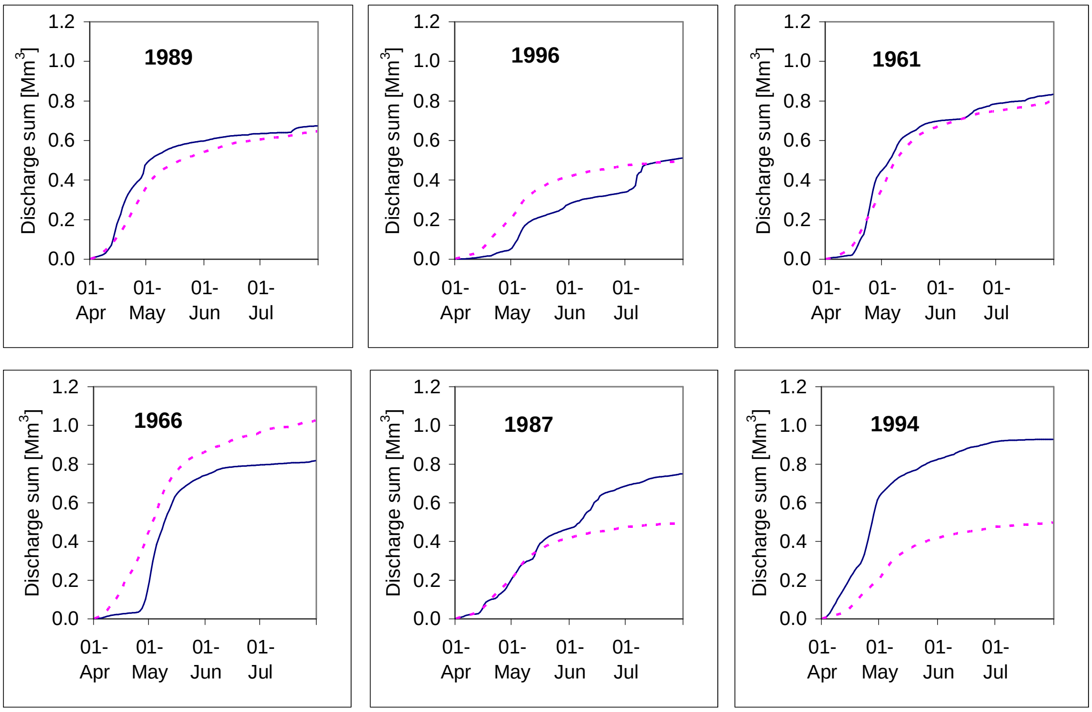


Figure 24. Six examples of streamflow volume forecasts for a lead-time of four months in Ruunapuro on April 1. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

The confusion matrix of the same case is shown in Table 13. The very wet years are mainly misclassified into a "wet" class. Otherwise, the forthcoming periods are decently classified (CEP=38%). Only a single, very bad classification error is made. In 1994 a very wet period is classified into a "very dry" class. As a consequence, the error of the streamflow volume forecast is large, as seen in Figure 24.

Table 13. The confusion matrix of the forecasts for a lead-time of four months in Ruunapuro basin on April 1 by using 4 classes and the MDC. $ASWE_{Ruunapuro}$, Fr_{field}, Fr_{forest} and $\sum Q2_{Ruunapuro}$ were used as features.

	1	*2*	*3*	*4*
1	**4**	1	0	0
2	3	**7**	2	0
3	1	1	**9**	1
4	1	0	4	**2**

For comparison, the same data set was used to estimate multiple linear regression equations for forecasting the forthcoming streamflows. The leave-one-out method was used to study the accuracy of the method. Table 14 shows the results. A statistically significant linear regression model was not found for forecasting Q_{Apr}. The regression coefficients of the independent variables were not statistically significant. Thus neither of the model types can be used to forecast streamflow volumes of a time period of one month effectively without weather forecasts on April 1. For the streamflow volumes of the longer periods, significant equations were found, however. The R-squared criterion (R^2) of the forecasts varied between 0.50 and 0.35 depending of the forecast length. Thus, the results are slightly better than the ones of the new model type.

Table 14. The forecast accuracy of the multiple linear regression models in Ruunapuro on April 1. The independent variables used are marked with X.

Forecast length [d]	**Constant**	**$ASWE_{Ruunapuro}$**	**Fr_{forest}**	**Fr_{field}**	**$\Sigma Q2_{Ruunapuro}$**	**$GW_{Äijälä}$**	**$SM_{Äijälä}$**	**$\Sigma P_{Aug\text{-}Oct}$**	**R^2**	**μ [%]**	**σ**	**n**
30	-	-	-	-	-	-	-	-	-	-	-	-
60	X	X		X	X	X			0.48	+4	26	22
90	X	X				X			0.49	+5	29	26
120	X	X				X			0.50	+4	27	26
150	X	X			X				0.41	+4	23	43
180	X	X			X				0.35	+4	25	43

3.3.2 Ruunapuro basin, forecasts on October 1

In October, four possible features for the classification of the forecast periods are available: the accumulated streamflow of the period preceding the forecast date ($\sum Q_{Ruunapuro}$), the groundwater and soil moisture data in Äijälä ($GW_{Äijälä}$, $SM_{Äijälä}$) and the precipitation data in the Ruunapuro basin ($\sum P_{Jul\text{-}Sep}$). The accumulated precipitation of the period between July 1 and end of September was used based on the analysis of correlations. Because of the limited amount of soil moisture data (n=10 years), it is practically impossible to verify its usefulness in the application. The lack of data also limits the use of different methods and the number of classes in the model. To guarantee enough observations for each of the classes, the thresholds are selected differently compared with the case of forecasting on April 1. The 33% and the 67% percentiles of the discharge sum distribution are used for the case of three classes, the 25, 50 and 75% percentiles for the case of four classes and the 20, 40, 60, 80% percentiles for the case of five classes. It is not possible to divide the data into more than three classes when the soil moisture observations are used in the feature vector.

In Table 15 the correlation matrix between the available hydrologic variables on October 1 and the streamflow volumes of the forthcoming periods in Ruunapuro is presented. The highest correlations are around 0.5-0.6. The forthcoming streamflow volumes seem to be slightly linearly dependent on the $\sum P_{Jul\text{-}Sep}$, $\sum Q_{Ruunapuro}$ and soil moisture on October 1. The features available also correlate with each others. This is especially true for $\Sigma Q2_{Ruunapuro}$ and $\Sigma Q4_{Ruunapuro}$. Thus only one of the two is used in the application. Variances of the possible features within the classes are large. In addition, the average values of the features in different classes are relatively close to each other.

Table 15. Correlation matrix between the hydrological variables and the forthcoming discharge sum in Ruunapuro on October 1.

	Q_{Oct}	$Q_{Oct\text{-}Nov.}$	$Q_{Oct\text{-}Dec}$	$Q_{Oct\text{-}Jan}$	$Q_{Oct\text{-}Feb}$	$Q_{Oct\text{-}Mar}$	$\Sigma Q2_{Ruunapuro}$	$\Sigma Q4_{Ruunapuro}$	$GW_{Äijälä}$	$\Sigma P_{Jul\text{-}Sep}$	$SM_{Äijälä}$
Q_{Oct}	**1.00**										
$Q_{Oct\text{-}Nov}$	**0.89**	**1.00**									
$Q_{Oct\text{-}Dec}$	**0.79**	**0.95**	**1.00**								
$Q_{Oct\text{-}Jan}$	**0.75**	**0.91**	**0.98**	**1.00**							
$Q_{Oct\text{-}Feb}$	**0.72**	**0.87**	**0.96**	**0.99**	**1.00**						
$Q_{Oct\text{-}Mar}$	**0.66**	**0.81**	**0.90**	**0.93**	**0.97**	**1.00**					
$\Sigma Q2_{Ruunapuro}$	**0.38**	**0.36**	**0.40**	**0.42**	**0.41**	**0.38**	**1.00**				
$\Sigma Q4_{Ruunapuro}$	**0.52**	**0.52**	**0.53**	**0.54**	**0.52**	**0.48**	**0.91**	**1.00**			
$GW_{Äijälä}$	0.14	0.11	0.08	0.08	0.09	0.13	**0.50**	**0.55**	**1.00**		
$\Sigma P_{Jul\text{-}Sep}$	**0.55**	**0.59**	**0.61**	**0.62**	**0.61**	**0.58**	**0.70**	**0.73**	0.29	**1.00**	
$SM_{Äijälä}$	**0.65**	0.48	0.51	0.52	0.46	0.30	0.62	**0.85**	0.39	0.36	**1.00**

For models using three classes, the lowest estimated CEPs are less than 50% for each of the forecast lengths (Table 16). At the same time, the standard deviations of the relative forecast error (σ) are large (σ>60%). However, this figure is strongly affected by the very dry period in 2002. Even if classifying this year correctly as dry, the relative forecast error is large. When omitting this year, σ is slightly over 40% and the average error (μ) decreases closer to zero. The increase of the number of classes increased the estimated CEPs of the models and did not improve forecast accuracy in the light of the relative errors.

Table 16. The forecast accuracy of the new model in Ruunapuro on October 1. The features used are marked with X.

Forecast length [d]	Number of classes	Pattern reg. algorithm	ΣQ_{2weeks}	ΣQ_{4weeks}	$GW_{Äijälä}$	$SM_{Äijälä}$	$\Sigma P_{Jul\text{-}Sep}$	CEP	R^2	μ [%]	σ	n
30	3	MDC	X				X	40	0.09	+6	66	45
	4	1-NNR			X	X		30	0.72	-5	30	10
60	3	MDC	X				X	38	0.23	+13	64	45
90	3	MDC		X			X	38	0.14	+9	67	45
120	3	MDC	X				X	47	0.13	+10	68	45
150	3	MDC	X				X	40	0.07	+11	68	45
	3	MDC		X		X		30	-0.70	-9	36	10
180	3	1-NNR					X	47	-0.29	+19	108	45

In general, the best individual feature is $\sum P_{Jul\text{-}Sep}$. Ten years of available soil moisture data is such a short time-series that it is impossible to verify the usefulness of the soil moisture observations in the application. However, the results of using this data are promising as seen from the results of the two models with low CEPs shown in Table 16. If soil moisture data were not used, the best performance of the model type was attained for the forecasts of a time period of two and three months. By using $\sum Q_{Ruunapuro}$ and $\sum P_{Jul\text{-}Sep}$ as features, MDC and three classes, the CEP was 38%. The R^2 was 0.23 for the forecasts of a period of two months and 0.14 for the period of three months. At the same time, σ was over 60% for both of the models. In Table 17 the confusion matrix of the forecasts of a time period of two months is shown. Above mentioned variables were used as features. Although the overall classification error is large, it is very likely that a period classified as a dry one will become a dry or a normal period. Similarly a period classified as wet will very likely become a wet or a normal period.

Table 17. The confusion matrix of the forecasts for a lead-time of two months in Ruunapuro on October 1 by using 3 classes and the minimum distance classifier. $\sum Q_{Ruunapuro}$ and $\sum P_{Jul\text{-}Sep}$ were used as features.

	1	*2*	*3*
1	**12**	3	0
2	5	**9**	6
3	1	2	**7**

For comparison, multiple linear regression equations for the forthcoming inflows were estimated. The results are shown in Table 18. For all of the forecast lengths, the regression model was forced through the origin and $\sum P_{Jul\text{-}Sep}$ was the only independent variable. This was the result of the backward elimination procedure. The R^2 of the models vary between 0.24 and 0.32. Hence, the linear regression equations are better in the light of R^2 compared with the new model, but σ is of the same order of magnitude. Again, σ and μ are sensitive to large relative errors corresponding to small streamflows.

Table 18. The forecast accuracy of the multiple linear regression models in Ruunapuro on October 1. The independent variables used are marked with X.

Forecast length [d]	Constant	$\Sigma Q2_{Ruunapuro}$	$\Sigma Q4_{Ruunapuro}$	$GW_{Äijälä}$	$SM_{Äijälä}$	$\Sigma P_{Jul\text{-}Sep}$	R^2	μ [%]	σ	n
30						X	0.24	+44	94	45
60						X	0.28	+29	67	45
90						X	0.31	+26	69	45
120						X	0.32	+25	68	45
150						X	0.32	+23	67	45
180						X	0.29	+21	62	45

3.3.3 Heinäjoki basin, forecasts on April 1

In Heinäjoki, six possible features are available for forecasting on April 1: the areal snow water equivalent ($ASWE_{Heinäjoki}$), the frost depth in field (Fr_{field}) and forested (Fr_{forest}) sites in the Heinäjoki basin, the discharge sum of the period preceding the forecast date ($\sum Q_{Heinäjoki}$), the state of the groundwater table in Vehkoo (GW_{Vehkoo}) and the accumulated precipitation of the period preceding the forecast date in the Heinäjoki basin ($\sum P_{Aug\text{-}Oct}$). The precipitation sum of the period between the August 1 and the end of October in the preceding year was used. The correlation matrix of the forthcoming streamflow volumes and the hydrological variables on April 1 is presented in Appendix E. The estimated correlation coefficients between $ASWE_{Heinäjoki}$ and the forthcoming streamflow volumes are significant. These correlations for the periods of two months and longer are as large as 0.61-0.72. For the other variables, the estimated correlation coefficients with the forthcoming streamflow volumes are statistically insignificant at 95% confidence level.

Also the within class variances and the between class distances were studied. For the forecast period of one month, the variances of the possible features within the classes are large. In addition, the averages of the features between the classes do not differ significantly. This is true for each of the feature candidates. For longer forecast periods, the average values of $ASWE_{Heinäjoki}$ between the classes are different. Variances of the features inside the classes are large, however.

In Table 19 the results of the best models are shown for Heinäjoki on April 1. The models shown were selected based on the lowest estimated CEPs. $ASWE_{Heinäjoki}$ is the most important feature. The worst results are again attained for the forecasts of a time period of one month. Although the estimated CEP was not larger than 35%, the relative forecast errors were of concern. The streamflow forecasts based on this classifier were biased (+41%) and σ was as large as 147%. These figures are strongly affected by the error of the correctly classified but very dry period in 1985. Although correctly classified, the forecast is over seven times larger than the observed streamflow volume (0.23 Mm^3 vs. 0.03 Mm^3) showing the evident weakness of the method to forecast satisfactorily extremely dry or extremely wet periods. By omitting the year 1985 from the results, σ is 111% and μ=+26%. For the longer periods, the mean errors are close to zero for the best models and σ varies between 20 and 30% (Table 19). By using three classes, the R^2 of the models is between 0.27 and 0.51.

Table 19. The forecast accuracy of the new model type in Heinäjoki on April 1. The features used are marked with X.

Forecast length [d]	Number of classes	Pattern reg. algorithm	$ASWE_{Heinäjoki}$	Fr_{forest}	Fr_{field}	$\Sigma Q2_{Heinäjoki}$	$\Sigma Q4_{Heinäjoki}$	GW_{Vehkoo}	$\Sigma P_{Aug-Oct}$	CEP [%]	R^2	μ [%]	σ	N
30	3	3-NNR	X	X		X				35	-0.17	+41	147	40
60	3	MDC	X			X		X		28	0.51	+3	22	25
90	5	MDC	X							49	-0.08	-3	26	43
120	3	1-NNR	X		X	X				28	0.27	+2	20	40
150	3	3-NNR	X		X		X			20	0.34	-2	21	40
180	3	3-NNR	X		X		X			25	0.36	-2	21	40

In Table 20 a confusion matrix of the forecasts for a time period of six months is shown. The model was based on three classes and on the use of the *3*-NNR. $ASWE_{Heinäjoki}$, Fr_{field} and $\sum Q4_{Heinäjoki}$ were used as features. As seen, the dry and normal periods are well classified. The problems are related to the wet periods. In Figure 25 six examples of the final discharge forecasts are given. In the first row, examples of the forecasts based on correct classification and in the lower row forecasts based on misclassification are shown. Some of the forecasts are very good (1976, 1986), but for some of the correctly classified periods, the timing of the discharge peaks is biased (1988). The discharge time-series in 1987 was unusual because of the heavy rainfalls during the summer and thus daily discharge forecasts were poor especially for August and September. In 1999 and 1984, the periods were simply misclassified.

Table 20. The confusion matrix of the forecasts for a lead-time of six months in Heinäjoki on April 1 by using 3 classes and the *3*-NNR. $ASWE_{Heinäjoki}$, Fr_{field} and $\sum Q4_{Heinäjoki}$ were used as features.

	1	*2*	*3*
1	**7**	1	0
2	2	**20**	3
3	0	4	**3**

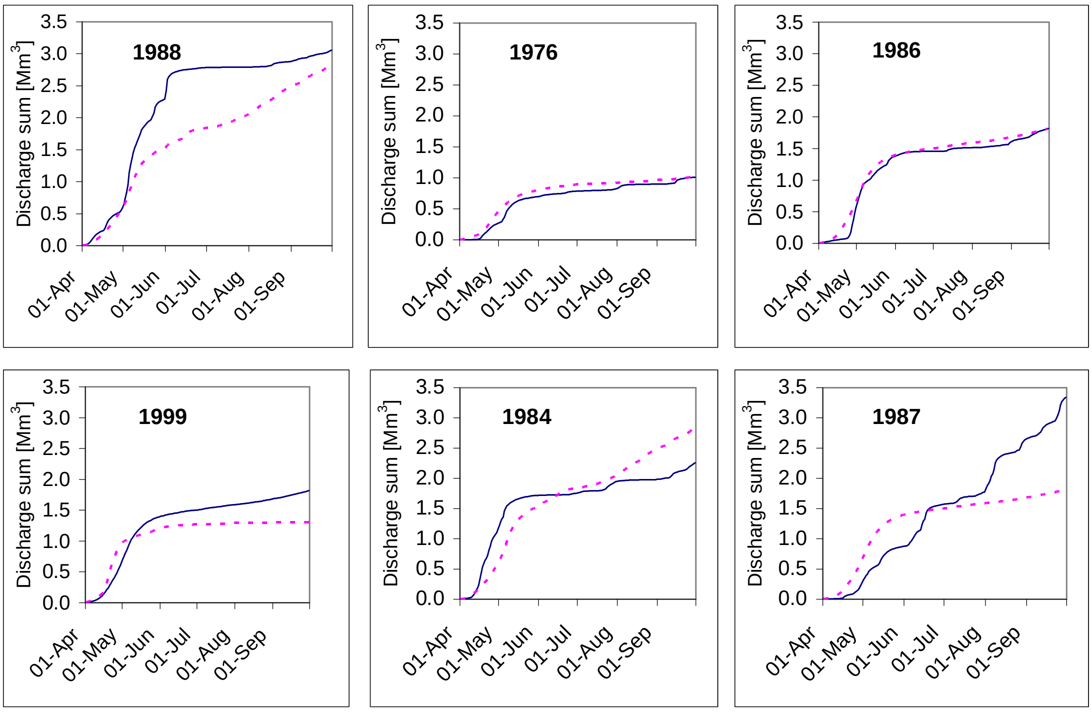


Figure 25. Six examples of streamflow volume forecasts for a lead-time of six months in Heinäjoki on April 1. Darker line is the observation and lighter (dashed line) is the forecast.

To compare the accuracy of the models, the same data set was used to estimate multiple linear regression models and the accuracy of the models was studied by using the leave-one-out method. The results are shown in Table 21. The R^2 of the forecasts varied between 0.02 and 0.54 depending on the forecast length. Thus, the accuracy was of the same order of magnitude or slightly better than for the new model type. $ASWE_{Heinäjoki}$ was the most important independent variable in the model. As distinct from the new model type, also $\sum P_{Aug\text{-}Oct}$ was used as an independent variable in most of the models.

Table 21. The forecast accuracy of the multiple linear regression models in Heinäjoki on April 1. The independent variables used are marked with X.

Forecast length [d]	Constant	$ASWE_{Heinäjoki}$	Fr_{forest}	Fr_{field}	$\Sigma Q2_{Heinäjoki}$	$\Sigma Q4_{Heinäjoki}$	GW_{Vehkoo}	$\Sigma P_{Aug\text{-}Oct}$	CEP [%]	R^2	μ [%]	σ	N
30		X				X				0.02	+53	201	42
60		X				X		X		0.54	+3	20	38
90		X						X		0.50	+2	22	38
120		X						X		0.45	+2	23	38
150		X						X		0.38	+3	24	38
180		X						X		0.35	+4	25	38

3.3.4 Heinäjoki basin, forecasts on October 1

In October only three features are available for long-term streamflow forecasting: the streamflow volume of the period preceding the forecast date ($\sum Q_{Heinäjoki}$), the state of the groundwater level in Vehkoo (GW_{Vehkoo}) and the accumulated precipitation between July 1 and the end of September ($\sum P_{Jul\text{-}Sep}$). Similarly to case Ruunapuro on October 1, the 33% and 67% percentiles of the fitted normal distributions are used for the case of three classes, the 25, 50 and 75% percentiles for the case of four classes and the 20, 40, 60, 80% percentiles for the case of five classes to guarantee enough observations for each of the classes. The correlation matrix between the latest observations of the hydrological variables on October 1 and the forthcoming streamflow volumes in the Heinäjoki stream is given in Table 22. A positive correlation coefficient between each of the variables was found, although the correlations between GW_{Vehkoo} and forthcoming inflows were not statistically significant at 95% confidence level.

Table 22. Correlation matrix between the hydrological variables and the forthcoming discharge sum in Heinäjoki on October 1.

	Q_{Oct}	$Q_{Oct\text{-}Nov}$	$Q_{Oct\text{-}Dec}$	$Q_{Oct\text{-}Jan}$	$Q_{Oct\text{-}Feb}$	$Q_{Oct\text{-}Mar}$	$\Sigma P_{Jul\text{-}Sep}$	$\Sigma Q2_{Heinäjoki}$	$\Sigma Q4_{Heinäjoki}$	GW_{Vehkoo}
Q_{Oct}	**1.00**									
$Q_{Oct\text{-}Nov}$	**0.86**	**1.00**								
$Q_{Oct\text{-}Dec}$	**0.72**	**0.94**	**1.00**							
$Q_{Oct\text{-}Jan}$	**0.75**	**0.91**	**0.98**	**1.00**						
$Q_{Oct\text{-}Feb}$	**0.73**	**0.89**	**0.96**	**0.99**	**1.00**					
$Q_{Oct\text{-}Mar}$	**0.69**	**0.83**	**0.91**	**0.94**	**0.98**	**1.00**				
$\Sigma P_{Jul\text{-}Sep}$	**0.33**	**0.42**	**0.45**	**0.48**	**0.47**	**0.42**	**1.00**			
$\Sigma Q2_{Heinäjoki}$	**0.36**	**0.35**	**0.32**	**0.35**	**0.33**	**0.29**	**0.78**	**1.00**		
$\Sigma Q4_{Heinäjoki}$	**0.54**	**0.52**	**0.46**	**0.48**	**0.47**	**0.41**	**0.79**	**0.90**	**1.00**	
GW_{Vehkoo}	0.28	0.39	0.38	0.35	0.36	0.36	**0.54**	**0.41**	**0.46**	**1.00**

The results for the models giving the lowest CEPs are shown in Table 24. For each of the forecast periods, a model was found to obtain an estimated CEP that is less than 50%. The relative forecast errors are large, however. The accuracy is slightly better compared with the case of Ruunapuro on October 1. The lowest σ is 38% and the highest R^2=0.45. This is the case for the model selected to forecast the streamflows of a time period of two months (see confusion matrix in Table 23). For the forecasts of a time period of three and five months, the chosen models seem to give biased forecasts ($\mu \neq 0$). $\sum Q_{Heinäjoki}$ was the most important feature.

Table 23. The confusion matrix of the forecasts for a lead-time of two months in Heinäjoki on October 1 by using 3 classes and the MDC. $\sum Q4_{Heinäjoki}$ was used as an only feature.

	1	*2*	*3*
1	**15**	2	0
2	6	**4**	3
3	0	7	**6**

Table 24. The forecast accuracy of the new model in Heinäjoki on October 1. The features used are marked with X.

Forecast length [d]	Number of classes	Pattern reg. algorithm	$\Sigma Q2_{Heinäjoki}$	$\Sigma Q4_{Heinäjoki}$	GW_{Vehkoo}	$\Sigma P_{Jul-Sep}$	CEP	R^2	μ [%]	σ	n
30	3	MDC		X			35	0.37	+1	61	43
60	3	MDC		X			42	0.45	-2	38	43
90	3	3-NNR	X				44	-0.11	+18	78	43
120	4	MDC		X		X	49	0.13	+2	51	39
150	3	MDC		X	X		44	-0.08	+13	57	25
180	3	MDC		X			43	0.16	+5	48	42

For comparison, linear regression equations for forecasting the streamflow volumes were estimated and their accuracies were studied by using the same data set. Table 25 shows the results. It seems that the new approach gives better forecasts than linear regression models for Heinäjoki on October 1. Differences are most evident for the forecast period of two months. However, the elimination of a one very poor forecast from the pool concerning the linear regression equation increased the value of R^2 from -0.03 to 0.34. Thus, the goodness-of-fit criterion is sensitive to individual observations.

Table 25. The forecast accuracy of the multiple linear regression models in Heinäjoki on October 1. The features used are marked with X.

Forecast length [d]	Constant	$\Sigma Q2_{Heinäjoki}$	$\Sigma Q4_{Heinäjoki}$	GW_{Vehkoo}	$\Sigma P_{Jul-Sep}$	R^2	μ [%]	σ	n
30	X		X			0.09	+54	111	43
60	X		X			-0.03	+28	68	43
90	X		X			-0.08	+32	77	43
120	X		X			-0.07	+30	74	43
150	X		X			-0.07	+26	70	43
180	X		X			-0.09	+28	75	43

3.4 Results for Lake Pyhäjärvi

Lastly, the accuracy of the forecast method was evaluated in the case study of Lake Pyhäjärvi. The lake is large compared with its basin and evaporation from the lake surface is the dominant factor in the water balance of the lake during the summer months. Because of the low lake percentage and the relatively short lags in the basin, the nature of the case study is somewhere between the study of Lake Päijänne and the two small basins, reminding more of the latter. The inflow to Lake Pyhäjärvi was forecast on two dates, on April 1 and on October 1 up to six months ahead.

3.4.1 Forecasts on April 1

Five features were available for inflow forecasting on April 1: the areal snow water equivalent on the forecast date ($ASWE_{Pyhäjärvi}$), the groundwater observation in Oripää station ($GW_{Oripää}$), the inflow and the precipitation sum of the preceding period ($\sum Q4_{Pyhäjärvi}$, $\sum P_{Sep\text{-}Oct}$) and the seasonal station based *NAO* indices of the season from December to February ($NAO_{Dec\text{-}Feb}$). Table 26 shows the correlation matrix. As can be seen, only the areal snow water equivalent has a highly significant linear connection with the forthcoming inflow volumes. It is noteworthy that a high correlation (r=0.37) was also found between the *NAO* indices and $\sum Q4_{Pyhäjärvi}$, the inflow sum of the lake in March.

Table 26. Correlation matrix between the hydrological variables and the forthcoming inflow sum in Lake Pyhäjärvi on April 1.

	Q_{Apr}	$Q_{Apr\text{-}May}$	$Q_{Apr\text{-}Jun}$	$Q_{Apr\text{-}Jul}$	$Q_{Apr\text{-}Aug}$	$Q_{Apr\text{-}Sep}$	$\Sigma Q4_{Pyhäjärvi}$	$ASWE_{Pyhäjärvi}$	$GW_{Oripää}$	$\Sigma P_{Sep\text{-}Oct}$	$NAO_{Dec\text{-}Feb}$
Q_{Apr}	**1.00**										
$Q_{Apr\text{-}May}$	**0.84**	**1.00**									
$Q_{Apr\text{-}Jun}$	**0.75**	**0.94**	**1.00**								
$Q_{Apr\text{-}Jul}$	**0.69**	**0.86**	**0.93**	**1.00**							
$Q_{Apr\text{-}Aug}$	**0.59**	**0.75**	**0.85**	**0.94**	**1.00**						
$Q_{Apr\text{-}Sep}$	**0.55**	**0.67**	**0.78**	**0.87**	**0.96**	**1.00**					
$\Sigma Q4_{Pyhäjärvi}$	-0.16	-0.26	-0.27	**-0.32**	-0.27	-0.26	**1.00**				
$ASWE_{Pyhäjärvi}$	**0.63**	**0.76**	**0.72**	**0.71**	**0.63**	**0.57**	**-0.40**	**1.00**			
$GW_{Oripää}$	0.08	0.09	0.09	-0.01	0.05	0.06	0.12	0.06	**1.00**		
$\Sigma P_{Sep\text{-}Oct}$	0.02	0.20	0.35	0.35	**0.39**	0.37	0.11	0.29	**0.41**	**1.00**	
$NAO_{Dec\text{-}Feb}$	0.18	-0.09	-0.01	-0.04	-0.04	-0.07	**0.37**	-0.14	0.20	0.13	**1.00**

The results for the models giving the lowest estimated CEPs are shown in Table 27. The areal snow water equivalent is the most important feature. Generally, the lowest CEPs are around 30%. A single model was found where the estimated CEP is as low as 14%. The highest values of the R^2 are around R^2=0.5. The results corresponding to the different classification algorithms are similar. In Figure 26 some examples of the forecasts of a lead time of four months are shown. Classification was based on *1*-NNR, five classes and on a single feature, $ASWE_{Pyhäjärvi}$. In the upper row, forecasts based on correct classification are presented and forecasts in the lower row were based on misclassification. Generally, it is easy to see that evaporation from the lake surface significantly affects the net inflow during the summer months. On the other hand, in 1998, despite the relatively dry spring season, the net inflow sum increases throughout the summer and as a consequence, the forecast is poor at the end of the forecast period.

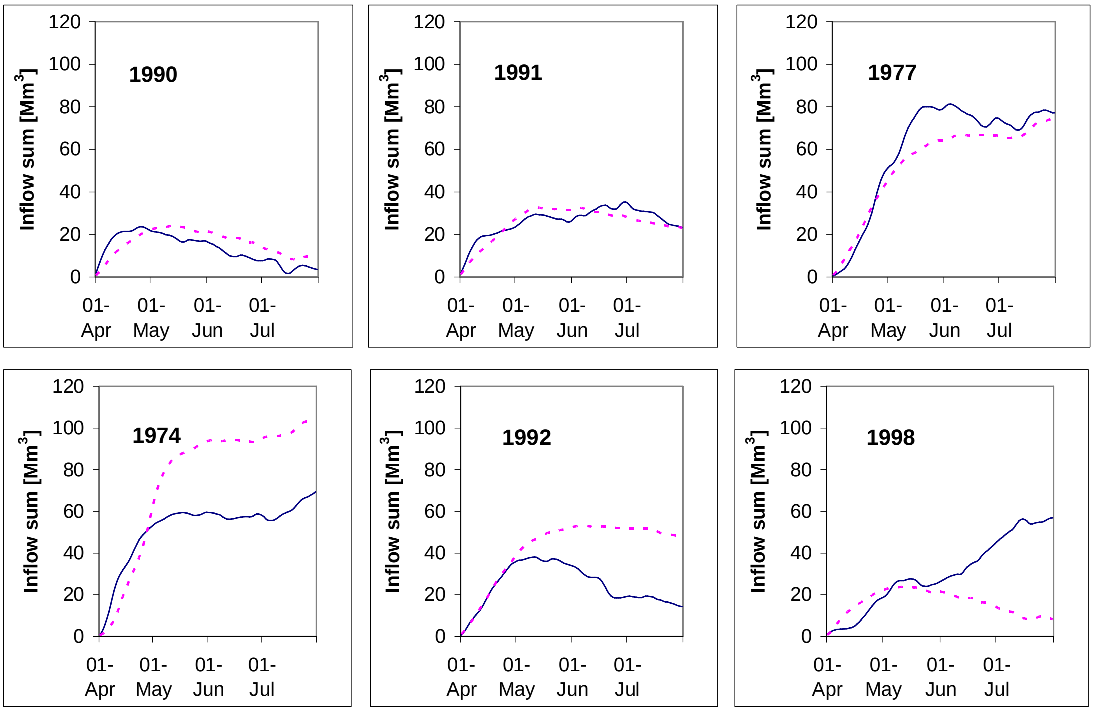


Figure 26. Six examples of inflow volume forecasts for a lead-time of four months in Lake Pyhäjärvi on April 1. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

The accuracy of the new model type was also compared with that of multiple linear regression models estimated by using the same data set and the leave-one-out method. The results concerning the linear regression models are shown in Table 28. By comparing the values of the R-squared criterion, model types seem to give results of the order of the same accuracy. For both of the models σ increases clearly as the forecast period lengthens. At the same time, however, the R^2 remains quite the same. This is due to the characteristic of σ to overweight the large relative errors of the small inflow volumes.

Table 27. The forecast accuracy of the new model type in Lake Pyhäjärvi on April 1. The features used are marked with X.

Forecast length [d]	Number of classes	Pattern reg. algorithm	ASWE	$GW_{Oripää}$	$\Sigma Q4_{Pyhäjärvi}$	$NAO_{Dec-Feb}$	$\Sigma P_{Sep-Oct}$	CEP	R^2	μ [%]	σ	n
30	3	3NN	X					26	0.31	-2	37	38
60	3	NN	X					26	0.36	+11	55	38
60	4	NN	X					32	0.52	+4	50	38
90	3	MDC	X	X				31	0.36	-2	50	29
120	3	3NN	X		X		X	30	0.13	+25	117	27
120	5	NN	X					45	0.40	+16	67	38
150	3	NN	X	X			X	27	0.24	+28	92	26
180	3	NN		X				14	0.25	+33	124	28
180	3	MDC	X	X	X	X	X	35	0.40	+13	54	26

Table 28. The forecast accuracy of the multiple linear regression models in Lake Pyhäjärvi on April 1. The independent variables used are marked with X.

Forecast length [d]	Constant	ASWE	$GW_{Oripää}$	$\Sigma Q4_{Pyhäjärvi}$	$NAO_{Dec-Feb}$	$\Sigma P_{Sep-Oct}$	R^2	μ [%]	σ	n
30	X	X			X		0.36	+15	49	37
60		X	X				0.48	+16	50	34
90	X	X					0.47	+22	69	38
120	X	X					0.43	+46	142	38
150		X				X	0.43	+60	154	27
180		X				X	0.36	+55	142	27

3.4.2 Forecasts on October 1

Only four possible features were available for forecasting on October 1 in Lake Pyhäjärvi: the inflow and the precipitation sum of the period preceding the forecast date ($\sum Q_{Pyhäjärvi}$ and $\sum P_{Jun\text{-}Sep}$), the groundwater level observation in Oripää ($GW_{Oripää}$) and the seasonal station based NAO index for the season from July to September ($NAO_{Jul\text{-}Sep}$). For the case of three classes, the 33% and 67% percentiles were used as thresholds, for that of four classes the 25%, 50% and 75% percentiles and for that of five classes the 20%, 40%, 60%, and 80% percentiles. Based on the correlations, the precipitation sum of the period between June 1 and September 30 and the inflow sum of the period of four weeks preceding the forecast date were used ($\sum Q4_{Pyhäjärvi}$). The correlation matrix for the chosen features is presented in Table 29. The most significant correlation coefficients with the forthcoming inflows were found for the $\sum Q4_{Pyhäjärvi}$. Positive correlations coefficients were also found between the forthcoming inflows and the other possible features but they are mainly not significant at 95% confidence level.

Table 29. Correlation matrix between the hydrological variables and the forthcoming inflow sum in Lake Pyhäjärvi on October 1.

	Q_{Oct}	$Q_{Oct\text{-}Nov}$	$Q_{Oct\text{-}Dec}$	$Q_{Oct\text{-}Jan}$	$Q_{Oct\text{-}Feb}$	$Q_{Oct\text{-}Mar}$	$\Sigma Q4_{Pyhäjärvi}$	$GW_{Oripää}$	$\Sigma P_{Jun\text{-}Sep}$	$NAO_{Jul\text{-}Sep}$
Q_{Oct}	**1.00**									
$Q_{Oct\text{-}Nov}$	**0.81**	**1.00**								
$Q_{Oct\text{-}Dec}$	**0.75**	**0.93**	**1.00**							
$Q_{Oct\text{-}Jan}$	**0.71**	**0.84**	**0.95**	**1.00**						
$Q_{Oct\text{-}Feb}$	**0.68**	**0.75**	**0.84**	**0.93**	**1.00**					
$Q_{Oct\text{-}Mar}$	**0.64**	**0.66**	**0.73**	**0.82**	**0.95**	**1.00**				
$\Sigma Q4_{Pyhäjärvi}$	**0.45**	**0.44**	**0.42**	**0.43**	**0.43**	**0.37**	**1.00**			
$GW_{Oripää}$	0.19	0.24	0.14	0.21	0.20	0.15	0.16	**1.00**		
$\Sigma P_{Jun\text{-}Sep}$	0.37	0.32	0.27	0.28	0.32	0.32	**0.64**	**0.57**	**1.00**	
$NAO_{Jul\text{-}Sep}$	0.03	0.12	0.15	0.26	**0.36**	**0.35**	0.05	**0.37**	0.14	**1.00**

In the application, no superior feature vector combinations for forecasting were found. The accuracy of the model was poor in the light of each of the goodness-of-fit criteria. However, the σ and μ are affected by single large relative errors in the forecasts of the small inflow sums. These small errors cause σ and μ to increase to such an extent that the interpretation of the results is difficult. On the other hand, also the values of the R^2-criterion were less than 0 for all of the forecast lengths as seen in Table 30. To compare the results, multiple linear regression models were estimated by using the same data set. Table 31 shows the results. They are slightly better in the light of the R-squared criterion compared with the new model type. The predictability of the forthcoming inflows is low, however, as seen from the low values of R^2. The values of σ and μ are weighted, also for the linear regression models, by few large relative errors concerning the close to zero inflow volumes.

Table 30. The forecast accuracy of the new model type in Lake Pyhäjärvi on October 1. The features used are marked with X.

Forecast length [d]	Number of classes	Pattern reg. algorithm	$\Sigma Q4_{Pyhäjärvi}$	$\Sigma P_{Jun\text{-}Sep}$	$GW_{Oripää}$	$NAO_{Jul\text{-}Sep}$	CEP	R^2	μ [%]	σ	N
30	3	NN			X		25	-0.49	+175	1020	28
30	4	NN			X		25	-0.54	+186	1098	28
60	5	MDC	X	X	X		59	-0.50	+25	107	29
90	4	NN			X		47	-0.91	+29	115	30
120	4	NN				X	43	-0.61	+31	89	37
150	5	MDC	X	X			59	-0.12	+5	48	29
180	3	NN			X		37	-0.43	+23	97	30

Table 31. The forecast accuracy of the multiple linear regression models in Lake Pyhäjärvi on October 1. The independent variables used are marked with X.

Forecast length [d]	Constant	$\Sigma Q4_{Pyhäjärvi}$	$\Sigma P_{Jun\text{-}Sep}$	$GW_{Oripää}$	$NAO_{Jul\text{-}Sep}$	R^2	μ [%]	σ	N
30			X			0.10	+359	1198	27
60	X	X				0.09	+80	279	39
90	X	X				0.05	+42	129	39
120	X	X				0.07	+29	85	38
150		X		X	X	0.19	+25	82	33
180	X		X	X	X	0.14	+19	65	29

3.5 Sensitivity analysis

The model is based on the classification of the forthcoming period into the supervised classes. These classes were established based on the estimated distributions of the streamflow volumes of the forecast periods. In some of the cases, the fitted normal distributions were used instead of more suitable gamma-distributions. Also the thresholds were subjectively chosen. No optimisation methods were used to select these thresholds based on some goodness-of-fit criteria. Now, it was studied how sensitive the method is to these selections. It is already known that the increase of the number of the classes would increase the accuracy of the forecasts that are based on a correct classification. However, at the same time the estimated CEP increases. This is due to the fact that the available features do not divide the data into clear classes.

By using the case study of Lake Päijänne on April 1, it was studied how sensitive the model is to the selection of the thresholds. The results by using the original thresholds were shown in Table 7 (page 64). Thresholds were now varied. The first example of the sensitivity of the model on thresholds is given in Table 32. Results were obtained by the model using a single feature, $W_{Konnevesi}$, a lead time of one month, five classes and *5*-NNR.

Table 32. The sensitivity of the results on the chosen thresholds (percentiles). The case study of a lead time of one month and a single feature, $W_{Konnevesi}$ in Lake Päijänne on April 1.

Thresholds (%-quantiles)	CEP [%]	R^2	μ	σ	n
10,30,70,90	40	0.39	6	30	95
20,40,60,80	42	0.35	4	35	95
5,25,75,95	32	0.44	4	35	95
10,25,75,90	31	0.45	6	35	95
15,30,70,85	46	0.25	6	35	95

As can be seen, the CEP varies between 31 and 46, R^2 between 0.25 and 0.45 and σ between 30 and 35. Thus, the order of magnitude of the results is similar but variations are considerable. In Table 33 another example is given. The model that gave the lowest CEP in forecasting the forecast period of 5 months is studied (The *1*-NNR, 3 classes and $GW_{Pieksämäki}$, as an only feature). Results (especially CEP and σ) are highly sensitive to the chosen thresholds. By chance, the thresholds originally used (20%, 80%) happened to give extremely good results. These results become much worse, however, after relatively small changes in the chosen thresholds

Table 33. The sensitivity of the results on the chosen thresholds. The case study of a lead time of five months in Lake Päijänne on April 1.

Thresholds	CEP	R^2	μ	σ	n
20,80	14	0.36	0	19	42
25,75	45	-0.07	-2	23	42
33,67	52	-0.39	0	27	42
15,85	12	0.24	2	23	42

Because the thresholds affect the CEP of the models, it should also be studied how much the thresholds affect the selection of the best model. Thus, the whole validation procedure and selection of the best models was repeated with different thresholds by using two case studies: by studying the forecasts of a time period of three months in Heinäjoki on April 1 and the forecasts of a time period of one month in Ruunapuro on October 1. Three classes were used in the analysis. The supervised classes were established by dividing the estimated distribution based either on the 20% and 80%, the 30% and 60%, the 33% and 67%, or the 40% and 70% percentiles. In Heinäjoki, independently of the chosen percentiles, the lowest estimated CEPs varied between 30 and 35%. At the same time σ varied between 19 and 22%. The feature combinations of the models giving the lowest CEPs were similar, but not always exactly equal. The ASWE was, however, part of each of the feature combinations giving the lowest CEPs.

In Ruunapuro on October 1, it was not possible to use the 20% and 80% percentiles of the normal distribution. The available time-series of the hydrological variables were such that the extreme classes would have contained only a few observations. The results for the other three pairs of percentiles were similar to each other. Independently of the percentiles, the lowest estimated CEPs were around 40% and the relative forecast errors remained large. The best feature combinations were based on the observations on precipitation and preceding streamflow.

The best results for different cases were given out in the previous chapters (Table 7, Table 10, Table 12, Table 16, Table 19, Table 24, Table 27 and Table 30). These results are sensitive to the chosen quantiles. By using different quantiles, the best models may be slightly different but generally the feature combinations remain similar including intuitively reasonable variables. The fact that the best feature combinations occasionally change with the chosen quantiles, confirm that the forecast power of variables is weak and the differences in the efficiency of the different variables in the classification are small. Usually, the values of the variables in different classes are overlapping.

3.6 Discussion

According to Lettenmaier and Wood (1993), long-term forecasting methods can be divided into three classes: index-variable, storage accounting and conceptual simulation. The WSFS of the Finnish Environment Institute (Vehviläinen, 1994) is a typical example of conceptual simulation, whereas linear regression models used in long-term inflow forecasting fall into the index-variable methods. These are the two types of models used in long-term inflow forecasting in Finland so far. In this study, a categorical long-term inflow forecast model was developed. The model is simple in terms of structure and can be classified into the index-variable methods. The focus was on inflow sum forecasts and thus neither the timing nor the quantity of the high and low flows was studied in detail.

New approach was highly motivated by the current operation policy of Lake Päijänne but the model is easy to implement into all kinds of basins. Today, Lake Päijänne is regulated based on the inflow sum forecast of the length of 2-6 months. The wetness of the forthcoming period (5 classes) is forecast and the objective water levels are set based on these forecasts. Thus, the structure of the developed forecast model (categorical forecasts) would be fit for the real-time operation of the lake. The new forecast model is based on an assumption that the current hydrological state of the basin could reveal the shape of the forthcoming hydrograph. Thus, the new model tries to utilise the conservative nature of the hydrological pattern in Finland. Long-term weather forecasts were not used in forecasting because of their unreliability. First effort was made, however, for utilising indices of North Atlantic Oscillation in long-term inflow forecasting in Finland.

Concepts of pattern recognition were used to produce categorical inflow forecasts. Supervised pattern recognition was used to classify a forthcoming forecast period into one of the classes describing the wetness of the period. In order to study the sensitivity of the forecast power to chosen classification algorithm, two algorithms were applied, *k*-NNR and minimum distance classifier. The former has been used earlier in discharge forecasting, for example, by Yakowitz and Karlsson (1987), Galeati (1990), Araghinejad et al. (2006) and Granz et al. (2005) but their approach was not based on categorical forecasting. They used *k*-NNR to select the observations from the historical records that most closely resemble the conditions preceding the forecast period. Locally weighted polynomials of the neighbours were then used to generate the mean of the streamflow forecast. Although in meteorological forecasting applications of categorical forecasting are common, applications of categorical streamflow forecasting are rare. Some examples are available, however (e.g. Piechota et al., 1998).

The success of the two classification algorithms, *k*-NNR and MDC, was almost identical. However, the minimum distance classifier seemed to be more reliable if only a few observations were available for each class. The value of *k* had little effect on the results when *k*-NNR was used, although for some feature combinations it was impossible to use $k>1$ because of the limited amount of data. Thus, the use of a low value of *k* was found reasonable in this study because of the low number of observations in each of the classes. Some examples were found, however, where results were better when larger values of *k* were used.

To compare the accuracy of the new forecast model and to ease the simulations of the lake-river systems in regulation planning, daily inflow forecasts were generated based on the categorical forecast. The inflow forecast was based on the inflow series of the years in the class in question (Equation 3-2). Thus, compared to the linear regression models, the model enables a logic and straightforward calculation of the daily inflow forecasts. In addition, the model is non-parametric and by using the leave-one-out method (cross-validation), the model is easy to validate by using the whole data set without re-optimisation of the parameters. On the other hand, in real-time forecasting, the confidence limits of the forecasts should be available. Although no theoretical basis for the confidence limits of the model was derived, the limits can be approximated based on the validation results: a suitable distribution can be fitted to the data of the forecast errors and it can be used to approximate the confidence limits. The forecast method has two obvious weaknesses compared to conceptual simulation and linear regression models. The model is unable to accurately forecast extremely high and low flows because of the structure of Equation 3-2. In addition, the same equation is averaging the forecasts of a chosen class and thus, the model occasionally does not take into account all the information given by the features. However, by this selection the structure of the model remains simple and thus, perhaps more attractive for the engineers responsible for inflow forecasting and operation of the lake-river systems.

In addition to the selection of the features, the classification algorithm and the number of classes, the thresholds for classifying the supervised patterns into different classes must be subjectively chosen when the model is applied. The thresholds could be optimised based on some goodness-of-fit criteria in the training set to minimise the errors of the inflow forecasts concerning the correctly classified patterns. In some of the cases, the thresholds were chosen in a way that a priori probabilities of the classes were unequal. Out of the two applied classifiers: the *k* nearest neighbours rule and the minimum distance classifier, especially the latter is based on an assumption about the equiprobable (a priori) classes. Thus, the classifiers were not used optimally. Furthermore, it was pointed out that the model is sensitive to the selection of the thresholds (Chapter 3.5). Thus, the modeller should be careful in this phase of the application.

The selection of the best models was mainly based on the estimated classification error probability. This criterion does not take into account the rank differences in classification errors or the number of observation used in validation. This might be one of the reasons for the problems related to the sensitivity of the models to the chosen quantiles. For a low number of observations, the increase in the CEP is relatively large if one additional observation is available or one of the originally correctly classified observations is misclassified after the change of the quantiles. In addition, the number of the periods on which the estimated CEPs were based, was not equal for all of the combinations. This might increase the quality of one combination compared to another. If several models gave equal CEPs, the other criterions were used for model selection. The models were also evaluated based on the relative errors of the forecasts and the R^2-criterion of the forecasts. For case studies, where small and close to zero values are handled, relative errors may be huge, although absolute errors would be reasonable in respect of the size of the reservoir (e.g Lake Pyhäjärvi study in October). Thus σ or μ proved not to be very good goodness-of-fit criteria in these types of case studies.

The discursion of the available data was also a problem in the model selection. Sometimes, the number of patterns available from the wettest and driest classes was only 0-5. Theoretically, the objects in the training set should be typical representations of the classes and several examples of each of the classes should also be available. Thus, it is reasonable to ask whether the few patterns in the training set in the application are enough for the proper use of the classifiers. Generally, the classification of the extreme periods succeeded quite well, even though only a few training patterns were available. Hence, the available observations have arguably been typical representatives of the extreme classes.

In Lake Päijänne, the accuracy of the model is good (Table 7, Table 10). On April 1, the areal snow water equivalent, the Pieksämäki groundwater level, the inflow volume of the forecast period of two weeks preceding the forecast date and the water level of Lake Konnevesi were used in the models with the lowest CEPs. In October, the inflow sum of the period of two weeks preceding the forecast date, the precipitation sum of the preceding period (May-September) and the water level of Lake Konnevesi were the most important features. In the light of the R^2, forecast accuracy was between 0.26 and 0.64 on April 1, being the lowest for the longest forecast lead times. On October 1 the R^2 varied between 0.70 and 0.86. The standard deviation of the forecast error was around σ=20% on both of the forecast dates and was not extremely sensitive to the forecast length.

In Ruunapuro, the estimated classification error probabilities of the best models on April 1 varied between 28 and 47% (Table 12). In the Heinäjoki stream, the CEPs were similarly 20-49% (Table 19). For both of the basins, the models were practically unbiased. An exception was the forecast model of a time period of one month. The standard deviation of the relative errors varied between 20 and 30% for the different forecast lengths. Based on the R-squared criterion, the forecast power of the model can be considered weak. The maximum R^2 is 0.51 for the forecasts of a time period of two months in Heinäjoki and the minimum as low as -0.60 for the forecasts of a time period of one month in Ruunapuro. On October 1, the lowest estimated CEPs varied between 30 and 49% and σ was almost without exceptions over 50% for both of the basins. At the same time, the R^2 varied between +0.72 and -0.70. Although the estimated classification error probabilities are large, most of the misclassifications are small. Often the periods are misclassified only by a single step. A high probability of classifying a dry period into the “dry” or “normal” class instead of the “wet” class is achieved. Similarly, a wet period is classified with a high probability into the “wet” or “normal” class.

Long-term discharge forecasting in the small basins is difficult. The lake percentage of the two small basins, Ruunapuro and Heinäjoki, is practically 0 and the areas of the basins are very small. Thus, the delays are very short. The forecast power of the current hydrological state of the basin is not sufficient, because the forthcoming weather conditions have a strong influence on the runoffs. For example, the estimated correlation coefficient between the streamflow volume and the precipitation sum for the period between April 1 and September 30 was 0.52 in the Ruunapuro basin and 0.75 in the Heinäjoki basin. Hence, quite naturally, the forecast errors of the new model were large. The method could be used to some extent for spring and summer forecasting, however, mainly because of the dependence between the discharge sum of the forthcoming period and the areal snow water equivalent in the basins. Such a good variable for forecasting on October 1 was not found. In the winter time, the weather conditions in the area seem to affect the discharges in the basins more than the state of groundwater table or the precipitation sum before the forecast period. The value of the soil moisture data in forecasting remains unclear, however, because of the short observation period. A significant correlation between the soil moisture data in Äijälä and the streamflow volume of the forthcoming month was found however, both on April 1 and on October 1. Generally, the accuracy of the model for forecasting the streamflow of the small experimental basins is not high enough so as to be reasonable to utilize these forecasts in forecasting the inflow to Lake Päijänne.

In the light of forecast accuracy, the results for the case study of Lake Pyhäjärvi are similar to those of the two small basins. The basin of the lake is small compared with the size of the lake. In addition, the evaporation from the lake complicates inflow forecasting when the weather forecasts are not used. Thus, both the forecast accuracy of the new method and the accuracy of the estimated linear regression models are moderate on April 1 and poor on October 1. The lowest estimated CEPs in the forecasts on April 1 varied from 14% up to 35%. At same time, the R^2 of the forecasts varied between 0.13 and 0.52, being the highest for the forecasts of a time period of two months. The standard deviations of the relative forecast errors (σ) were large (from 49 up to 154%) due to the overestimated inflow volumes of the very dry periods. On October 1, the model could not be used for forecasting the inflows to Lake Pyhäjärvi. The values of the R^2 of the forecasts were less than 0, and both σ and μ were very large. The results show the difficulties related to long-term inflow forecasting in Lake Pyhäjärvi. The forthcoming evaporation and precipitation are major factors in the water balance of the lake and therefore, the forecast power of the current hydrologic state of the basin is insufficient.

A more thorough study should be aimed at linking the climatology to the hydrological phenomena in large basins in Finland. Although the indices of North Atlantic Oscillation were utilised only in a single application of the new forecast model, several significant correlation coefficients were found between the inflow to Lake

Päijänne and the NAO indices (Appendix B). This endorses the observations of Uvo and Berndtsson (2002) who found highly significant correlations (up to 0.6) between the winter precipitation in southern Finland and the seasonal NAO index of a period between December and March. Thus it was presumed that inflows of the snowmelt season are correlated with the NAO index. In comparison, in Norway up to 55 % of the variance in streamflow can be explained by the variation of the NAO index (Cherry et al., 2005). Furthermore, in the Belarus part of the Baltic Sea basin significant correlations coefficients (about 0.2-0.3) were found between seasonal NAO indices and river discharges especially in winter (Danilovich et al., 2007). The NAO signal is strongest in winter (Hurrell et al., 2003a) and therefore it was not surprising that when forecasting autumn and winter inflows in the Lake Päijänne basin in October, the NAO indices were not included in the feature vectors.

By using the same data set for estimating the multiple linear regression models, it was possible to compare the accuracy of the new method with a well-known forecast approach. In Lake Päijänne, the forecast accuracy of the methods is quite similar, in the small basins the linear regression models are better and in Lake Pyhäjärvi, results are again similar. The results strengthen the view that, instead of a poor model structure, the poor forecast accuracy in the small basins and in Lake Pyhäjärvi is due more to the nature of the basins and the chosen features (no weather forecasts). Only a few times the feature combinations used for the new model were also the best set of independent variables in the multiple linear regression models. Often more variables were used in the new approach, and as a consequence, fewer observations (i.e. fewer years) were normally used to evaluate the accuracy. However, in Ruunapuro on April 1, for example, the same features were used and the results were better for the linear regression models. The reason could be the possibility to weight the independent variables differently in the regression equations; in the new model the variables were equally weighted.

Although a reliable comparison of the results with those of other studies is difficult, results of some long-term forecast studies are worth a mention. The multiple correlation coefficient for the multiple regression model by Virta (1969) for forecasting inflow of Lake Päijänne was R=0.96 for the period between April 16 and June 30. In the same study, the R was only slightly lower in summer and autumn for the monthly forecasts. These figures are based on the data sets used for parameter estimation and in addition, the observed values of the precipitation of the forecast period were used in model calibration. Thus these figures are not directly comparable with the results of this study. However, the aforementioned study combined with the results of this study confirm that the inflow to Lake Päijänne can be forecast relatively well for several months in advance. This is due to the long residence time of the basin.

Gürer (1975) fitted linear regression models to forecast spring and autumn discharge sums in three basins in Finland. The forecast periods and the study basins were different compared with this study. However, for spring flow the average error (standard error of estimate/average inflow) in the different basins varied between ± 9 and ± 18%. For seasonal summer and autumn inflows, the error was on an average ± 22% in the Kemihaara basin and ± 30% in Pielinen. For seasonal winter flow, the model had a ± 20% error in the Pielinen basin. These figures are based on the data that were used to calibrate the model.

Kuusisto used a conceptual rainfall-runoff model to forecast the inflow sum of a time period of six months on April 1 into Lake Saimaa (Kuusisto, 1978). The model was validated by using only two years. For 1974 the observed inflow sum was about the same as the 10-20% percentile of the forecast. The forecast accuracy was the best at the end of the period. For 1975 the relative error in the inflow sum forecast was 21% at the end of the period. Kuusisto compared the results with the ones from a linear regression model. Because only two years were available, Kuusisto was unable to make reliable conclusions. However, the essential differences were found only in the confidence limits of the forecasts: the limits were wider in the forecasts of the linear regression model. The WSFS of the Finnish Environment Institute is mainly used for real-time flood warning in short-term periods. In addition, the model is used for long-term forecasting to help the operation of the regulated lake-river systems. Unfortunately, thorough studies about the accuracy of the long-term forecasts of the WSFS have not been published. As a matter of fact, the number of studies about the operational accuracy of real-time forecast models is generally limited. However, e.g. Johnell et al. (2007) and Olsson and Lindström (2008) have evaluated the accuracy of the forecasts of a lead-time of 10 days concerning the operational HBV-96 (Lindström et al., 1997) model in Sweden. The errors of streamflow volume forecasts were not studied but the average bias of the daily forecasts errors varied between the range of -20% and +80%. Druce (2001) has analysed the accuracy of the seasonal inflow volume forecasts produced by an operational conceptual hydrologic model and compared the results with the ones of a regression model in Columbia River. Mean percentage errors of the forecasts of the conceptual model for a period between February and September were 3.37% on January 1 and 2.32% on February 1. At the same time, the coefficient of variation was 0.086 and 0.073, respectively. Generally, the mean forecasts of the regression model were slightly poorer. The comparison of the results is difficult because of the different performance measures used for evaluation. It seems, however, that the difference between the accuracy of simple models and conceptual simulation models in long-term forecasting is not especially large.

To sum up, the accuracy of the new model does not seem to differ significantly from that of the linear regression models in the case of long-term inflow volume forecasting to Lake Päijänne. The models were tested and compared, however, only on two dates. It turned out that, in addition to the areal snow water equivalent, also the groundwater levels, the observed inflows, the precipitation, the NAO indices and the water levels of the upstream lakes can be used to forecast inflows months in advance. Thus, it might be possible to use the model also on other dates, if the basin is large enough. For the small basins and Lake Pyhäjärvi, the areal snow water equivalent seems to be the only variable really valuable in long-term forecasting and thus the value of the model outside of the snowmelt season is limited without weather forecasts. However, due to the basin properties, the possibilities for long-term forecasting are poor irrespective of the forecast model.

Lastly, the structure of the forecast model is simple and thus it is not suffering from the scientific details and complicated simulations. Whether the accuracy of the model is still sufficient for the real-time operation of the lake-river system and how much the inaccuracy affects the success of the operation is studied in the next chapter.

4 Value of long-term inflow forecasts

4.1 Method

4.1.1 General methodology

The value of inflow forecasts has been discussed in several journal papers. The most cited paper is the one by Yeh et al. (1982) who studied the value of long-term inflow forecasts in the California State Water Project using artificial forecasts. Monthly (j) forecasts were generated by using the equation

$$F_j = Q_j + \varepsilon_j \cdot \sigma \cdot Q_j , \qquad \textbf{(4-1)}$$

where F_j is the forecast, Q_j the observed inflow volume of the month j and σ is the parameter describing forecast accuracy, a character of the forecast model. The forecast model was presumed unbiased and thereby the random number ε_j was set normally distributed N(0,1). By operating the studied reservoir system theoretically with different values of σ and with different forecast periods, it was possible to approximate the dependence of the value of inflow forecasts on their accuracy and length. The forecasts and the comparisons were based on the historical streamflow in 1914-1973. A similar approach was used when Mishalani and Palmer (1988) studied the value of inflow forecasts for the water supply of the Seattle metropolitan area in the United States. The approach is justified and intuitively attractive.

In this method, the results are dependent on the update frequency of the forecasts. If the forecast is updated every day (Equation 4-1), the effect of a single large forecast error on the regulation is small. This is due to the unbiased forecast model. In addition, the approach does not take into account the problems related to the timing of high and low flows during the forecast period. The correct timing of a flood season may not be a serious matter in large lakes. However, in the small ones, where the storage capacities are small, even a small error in the timing of the maximum flood may cause severe problems.

The aim of the current study is to approximate the dependence of the success of the regulation on the accuracy, length and update frequency of the inflow forecasts. The idea of Yeh et al. is used. As distinct from their approach, the forecast error is now generated for the whole forecast period at the same time, not individually for each of the months in the forecast period.

$$F = Q + \varepsilon \cdot \sigma \cdot Q \qquad \textbf{(4-2)}$$

Thus in Equation 4-2, F is the forecast and Q the observed inflow volume of the forecast period. The absolute error of the generated forecast is then uniformly divided over the whole forecast period. This makes it possible to simulate daily water levels and releases of the studied system.

The value of the forecasts is also studied in the case where forecast errors are lag-1 autocorrelated. New observations between two consecutive forecast dates rarely contain such information as to lead to a dramatic change in the long-term forecasts and their errors. Therefore, an unbiased model that has no autocorrelation between the forecast errors is unlikely to exist. To add autocorrelation into the errors of the artificial forecasts, a sequence of random numbers ε_j is generated by using the equation

$$\varepsilon_{j+1} = a_1 \cdot \varepsilon_j + \varepsilon\sqrt{\left(1 - a_1^2\right)}, \qquad \textbf{(4-3)}$$

where a_1 is the lag-1 autocorrelation coefficient between the forecast errors and ε is normally distributed N(0,1). It is easy to see that also ε_{j+1} is now N(0,1). When the effects of autocorrelation between the consecutive forecast errors are studied, the coefficient a_1=0.80 is used. The value was subjectively chosen, because no studies were found about the possible autocorrelation between the forecast errors. However, by selecting a large value for a_1, the effect of the additional autocorrelation should be distinguishable from the case of a_1=0.0.

The study is based on the theoretical operation of two different kinds of reservoir systems using artificial forecasts. By studying Lake Pyhäjärvi, the effect of forecast accuracy on the operation of a single reservoir system is studied. When studying the River Kymijoki system, the focus was on a multi-reservoir system. The simulation period in the case of Lake Pyhäjärvi is 1966-2004 and in that of River Kymijoki 1964-2004. These periods consist of all kinds of water years, from droughts (2002-2003) to very wet years (e.g.1974-1975). The forecast length in the study varies between 30 and 360 days and forecasts are updated every 15 days. Briefly, the basic algorithm is as follows:

1. By using the Equation 4-2, the inflow volume of the forecast period is generated.
2. The release sequence of the forthcoming period is optimised by using the inflow forecast and a release optimisation algorithm *simulated annealing.*
3. The system is operated by using the optimised release sequence and the *observed* inflow sequence until the next forecast date (the length of this period is the update frequency of the forecasts).
4. Move to step 1, unless the simulation period is at the end. It that case, move to step 5.
5. Calculate the value of the forecasts for the whole simulation period by using the optimised releases and the observed inflow.

Because of the randomly generated forecast errors, the simulation period was recalculated and operated 15 times and the average values are later analysed. The dependence between the update frequency of the forecasts and the success of the regulation are studied in the case study of Lake Pyhäjärvi by comparing the results of three separate simulations. In these simulations, new forecasts were generated either every 5, 15 or 30 days.

The value of σ is varied between 0.0 (perfect forecast) and 1.0 to study the effect of the forecast error on the value of the forecasts. The historical daily averages are also used as forecasts to give a base point to the study. If the average historical inflows give better results than the forecasts of an inaccurate forecast model, the model should not be used in real-time operation.

A heuristic optimisation algorithm, simulated annealing, is used to optimise the releases of the forecast period based on the given forecasts. The optimisation problem is to maximise the expected value of the objective function *G(R,S,I)*

$$\max_R E_I\left[G(R,S,I)\right] \tag{4-4}$$

where R is the release and S the storage of the reservoir. I is the inflow that is a stochastic variable with a density function $f(I)$. However, in this study the basic approach is such that the mean forecast is used in the operation of the systems without the confidence limits of the forecasts. Thus, the inflow I is assumed to be known. Thereby, it is supposed that the reservoir system is operated optimally based on a single forecast and the confidence limits of the forecasts or the ensemble forecast are not taken into account. Thus, a deterministic problem (Equation 4-5) is solved.

$$\max_R G(R,S,I) \tag{4-5}$$

The author is well aware of the uncertainties of the inflow forecasts in real-time operation of the systems: the optimisation problems are stochastic in nature. However, it is expected that the consequences of the decreasing accuracy of the forecasts are similar irrespective of the optimisation algorithm. To study whether this assumption is fair, the main part of the study in the case of Lake Pyhäjärvi is repeated by solving a stochastic problem (Equation 4-4). This problem can also be written as

$$\max_R \int_{-\infty}^{\infty} G(R,S,I)\,f(I)\,dI \tag{4-6}$$

By discretizing the density function of the inflow forecast, the problem is

$$\max_R \sum_{i=1}^{n} p_i G(R,S,I_i) \tag{4-7}$$

Now the uncertainties related to the inflow forecasts are taken into account. To shorten the time needed for the simulation, n=5 is used: the 10%, 30%, 50%, 70%, 90% percentiles of the mean inflow forecasts are used with equal probabilities p_i. The results based on this approach are presented in Chapter 4.2.4.

Between the two consecutive forecast dates, optimised releases are used and information on new inflow observations is not utilised. At the end of each of the forecast update periods (normally 15 days), the latest inflow observations are used to update the current real state of the system. To decrease the number of the variables in the optimisation, releases are constant over periods of five days. For example, when the length of a forecast period is 60 days, instead of 60 variables only 12 variables are used. Thus, releases can be increased or decreased only after a period of five days. This decreased the number of the decision variables and thus, the computing time needed in the optimisation. The assumption of using five-day periods can also be justified by studying the current operation of the lakes. Lake Päijänne, for example, is regulated on a monthly basis and daily regulation is not used.

4.1.2 Simulation model of Lake Pyhäjärvi

In the case study of Lake Pyhäjärvi, the system is a single reservoir operated by using a weir in the outlet in Kauttuankoski (Figure 27). Three hydropower plants are located downstream of Lake Pyhäjärvi in River Eurajoki: one in Pappilankoski, the second in Paneliankoski and the third in Eurakoski since 2006. The combined capacity of these power plants is 0.9 MW. The effects of the regulation of Lake Pyhäjärvi on these three hydropower plants downstream were not, however, taken into account in the study.

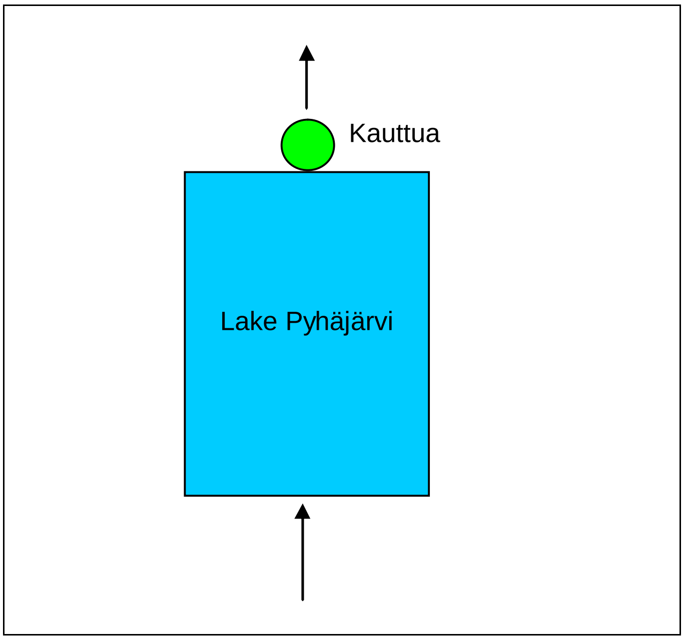


Figure 27. Flowchart of the Lake Pyhäjärvi simulation model.

The model of Lake Pyhäjärvi simulates daily water level changes of the lake based on given inflows and releases. The known linkage between the water level, the area and the volume of the lake (WAV curve) were utilised. Releases are optimised based on the inflow forecasts. Inflows are originally calculated by using the water balance equation. A constant head (10.9 m) is used in the Kauttuankoski power plant and the maximum discharge through the turbines is set to 6.0 m^3/s. The regulation licence sets some restrictions on releases. Firstly, the maximum release through the Kauttuankoski weir is 17 m^3/s. This is the maximum capacity of the downstream river reach. In addition, releases that are less than 2.0 m^3/s should be avoided. This is the case also during the dry seasons. The minimum release limit, 0.8 m^3/s, cannot be violated under any circumstances. This is due to water supply needs of the downstream plants. In addition, to accomplish a steady release series, the maximum release change between two consecutive periods of a length of five days was set to 2 m^3/s.

Because the net inflows are used in the model instead of approximating evaporation and rainfall separately, some bias may occur. The amount of evaporation (m^3/d) from the lake is dependent on the area of the lake (water level). When using optimised release sequences in the simulation, water levels will differ from the observed ones. Normally this would lead to changes in lake evaporation and precipitation and thus, in the net inflow. In the model, however, this phenomenon is not taken into account and originally approximated inflows are used. Because the lake is large, the relative errors in evaporation and precipitation are arguably small.

4.1.3 Simulation model of River Kymijoki

A flowchart describing the discrete water balance model of the River Kymijoki system is shown in Figure 28. Water levels of four regulated lakes: Päijänne, Ruotsalainen, Konnivesi and Pyhäjärvi in Iitti are simulated. At the same time, releases and discharges are simulated in a single control weir in Kalkkinen and 12 hydroelectric power plants in River Kymijoki. Arrows are used to describe the runoffs in the flowchart. The water balance equation was used to approximate the inflows into the system. Release from an upstream lake or a power plant equals the inflow of a next lake or a plant downstream if lateral inflows are not added. A daily time-step was used in the model.

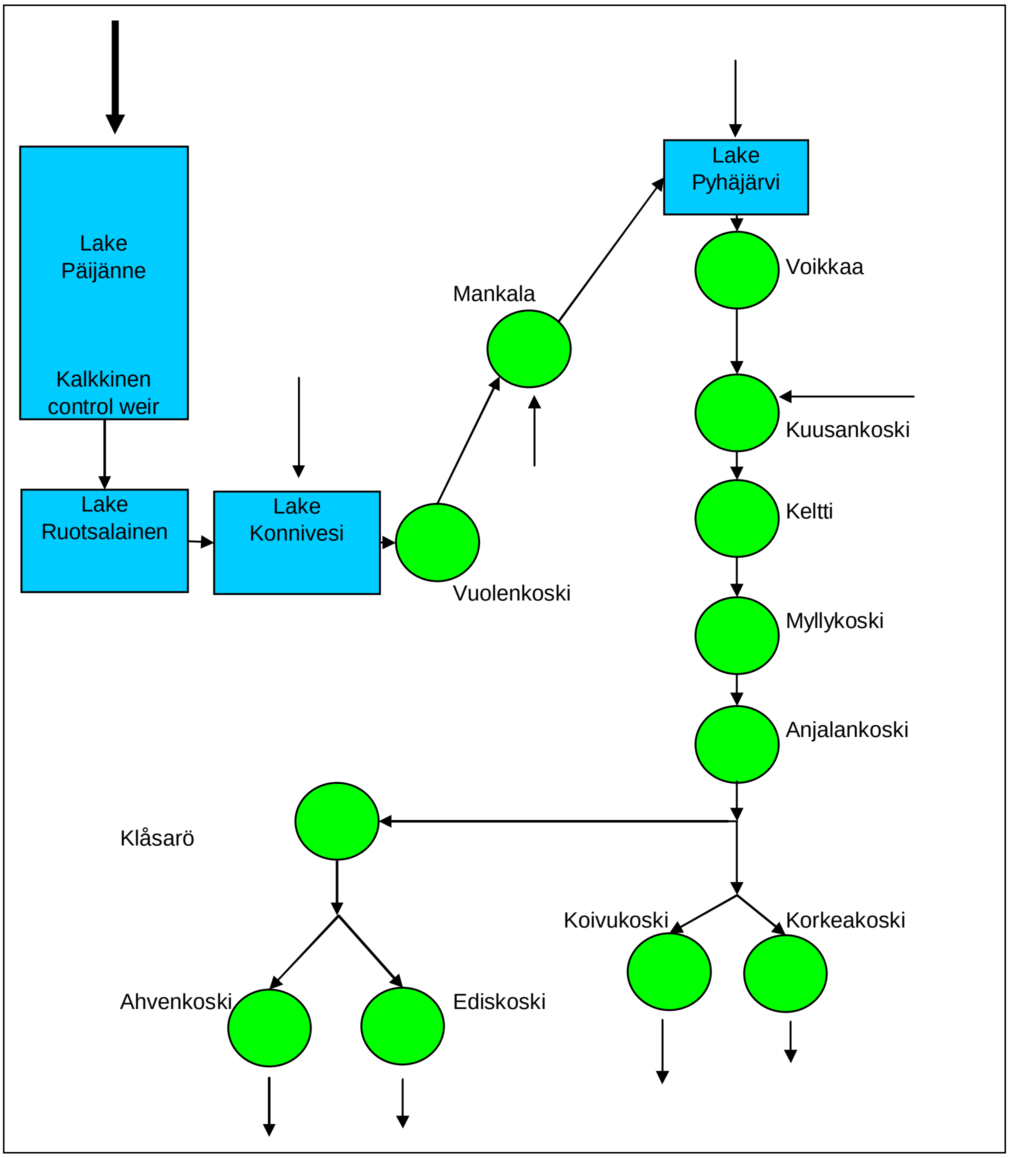


Figure 28. Flowchart of the River Kymijoki water balance simulation model.

The regulation of Lake Päijänne is based on the use of a control weir in Kalkkinen. In addition, the man-made canal joining Lake Päijänne and Lake Ruotsalainen can be used for regulation. However, about 70% of the outflow runs through the natural cascade in Kalkkinen and this outflow cannot be controlled (Figure 29). The outflow through the natural cascade was approximated in the model by using the rating curve of the cascade.


Figure 29. Kalkkinen natural cascade (left) and the regulation weir in Kalkkinen (right).

Discharge in the river reach between Lake Ruotsalainen and Lake Konnivesi (Jyrängönvirta) was simulated by using the available rating curve. The discharge is dependent on the water levels of both of the lakes. Downstream, River Kymijoki divides into several streams and the amount of water led to these streams is controlled. All instructions and restrictions given in the regulation licenses concerning the discharges in the different streams were also taken into account in the simulation model.

Several simplifications have been made to the model compared with the real lake-river system. Firstly, some small lakes (e.g. Lake Arrajärvi, Lake Tammijärvi) in the flow path of River Kymijoki are not simulated. Secondly, hydraulic models are not included. Therefore, water is flowing through the system without delays. In the model, the releases from the Voikkaa power plant will end up in the Baltic Sea during the same day. In reality, the delay between Lake Pyhäjärvi in Iitti (Voikkaa) and the Gulf of Finland is dependent on the discharge but is approximated to be around 57 to 80 hours or slightly more (National Board of Waters, 1972b).

In addition, only the most important inflows that enter the system are taken into account. The lateral water from the Channel of Mäntyharju flows into Lake Pyhäjärvi and water from the Channel of Valkeala enters the system just upstream of the Kuusankoski power plant. In addition, lateral water from Channel of Rääveli to Lake Konnivesi and that from the river reach between Lake Konnivesi and Lake Pyhäjärvi (River Arrajoki basin) are taken into account in the model. However, no inflows are added to the system downstream of the Kuusankoski power plant. Compared with the flow in the river, these additional inflows downstream of Kuusankoski were considered irrelevant and economically unsubstantial when releases were optimised upstream. This is supported by the fact that on average, 75% of the discharge in the outlets of River Kymijoki originates from Lake Päijänne (National Board of Waters, 1972b).

Because of the lack of a hydraulic model, the head at each of the power plants was set constant. An exception was made for the Vuolenkoski power plant, where the head was linearly dependent on the water level of Lake Konnivesi. This was due to the current release control policy. The lake is operated by keeping the water level close to the upper water level limit defined in the regulation license and thus by maximising the head in Vuolenkoski.

In Table 34, the characteristics of all of the power plants in River Kymijoki are presented. Efficiency factors of the power plants were set to η=0.83. The factor was kept constant at each of the power plants irrespective of the discharge.

Table 34. Statistics about the hydroelectric power plants in River Kymijoki (Järvinen and Marttunen, 2000).

Power plant	Head [m]	Maximum discharge through the turbines [m^3/s]
Vuolenkoski	3.5	370
Mankala	8.1	400
Voikkaa	9.0	400
Kuusankoski	9.2	400
Keltti	6.1	340
Myllykoski	7.0	470
Anjalankoski	9.7	435
Korkeakoski	12.5	95
Koivukoski	5.2	45
Klåsarö (Loosarinkoski)	3.2	180
Ahvenkoski	11.0	250
Ediskoski (Stockfors)	9.0	5.3

Just as in the Lake Pyhäjärvi model, evaporation is not calculated or forecast. This might cause some bias into the simulations when releases are fixed because of the changed water levels and lake areas. Changes are small compared with the total lake area, however, and thus error concerning evaporation is probably very small. Regardless of these assumptions and simplifications, the water balance model of the Kymijoki basin simulates the lake-river system well. The average annual energy production calculated by the model (1.29 TWh/a) is close to the 1.26 TWh/a given in the literature (The Ministry of Trade and Industry, 2005). In addition, water levels of the lakes in the model obey the observed values well, if the observed release sequences are used at the outlets of the lakes.

4.1.4 Release optimisation by using simulated annealing

4.1.4.1 Algorithm

Simulated annealing is used to find the optimal release sequence of the reservoir system based on the given inflow forecast. The analogy of an annealing process with optimisation is based on the analogy between the energy state of an annealing liquid and the value of the cost or objective function in the optimisation problem. In the process, the energy state and the value of the objective function should decrease. In this study, the aim is to maximize the value of the objective function and therefore, the algorithm is not used in its basic form. The description of the optimisation algorithm follows the presentation of Teegaravapu and Simonovic (2002). To maximize the objective function

1. Select variables that influence the system
2. Initialise the parameters of the algorithm
3. Introduce random generations to find a candidate solution (neighbour)
4. Obtain the performance measure G_{new} associated with the candidate solution using a simulation model and objective function
5. IF[$G_{new} > G_{old}$] THEN accept the new solution and set $G_{old} = G_{new}$

   ELSE accept/reject the move based on a stochastic criterion
6. Repeat steps 3-5 for L cycles
7. Lower "the temperature"
8. Store the best solution obtained so far
9. Repeat steps 3-8 until stopping criterion is met

The criterion for determining whether to accept or reject the candidate move in step 5 when $G_{new} < G_{old}$ is

$$\gamma < \min\left(1, e^{\left(-\left(G_{old} - G_{new}\right)/T\right)}\right) \qquad \textbf{(4-8)}$$

where γ is a uniformly distributed random number over the interval (0,1). If the equation is TRUE, the candidate solution is accepted (set $G_{old} = G_{new}$) and the value of the objective function decreases. The purpose of this step is to avoid situations where the optimisation algorithm would stick into a local maximum. If the equation is FALSE, the candidate solution is rejected. T in the equation is "temperature" that is decreased (step 7) as the optimisation proceeds. This assures that toward the end of the optimisation, the possibility to move into a poorer solution decreases. T is called temperature, because the algorithm tries to simulate the cooling of a glass mass to an optimal form.

Three parameters in the model must be selected subjectively based on the problem: the initial temperature, the parameter L, and the cooling schedule. In addition, the user has to select the stopping criterion. The larger the L and the lower the cooling velocity, the longer the time that the algorithm needs to find the solution. At the same time, the solution is probably closer to the global optimum. Therefore, the user often has to select between increased computer time and increased accuracy.

For the optimisation, an initial solution is needed. Three different strategies were used to find a valid initial solution in each of the optimisation problems. In the first strategy, the release sequence was generated in a stochastic manner and if necessary, it was changed as little as possible to fulfil the release restrictions. In the second strategy, releases were held equal to the latest observation of the preceding optimisation period during the new optimisation period, if this release sequence fulfilled all of the release restrictions. The third strategy used the current optimal solution as long as possible and after that a constant value was used until the end of the period. Because of the update frequency of 15 days, releases of only 15 days at the end of the new period have not been optimised in the previous optimisation task. Thus, this initial solution can be reasonably good if the forecasts of a time period of several months are studied and changes in the accuracy of the forecasts are small.

In step 7 of the algorithm, the value of T is lowered. It can be done in several ways. The most popular and probably the simplest schedule, an exponential cooling rule, is now used:

$$T_t = \alpha \cdot T_{t-1}. \qquad \textbf{(4-9)}$$

At each temperature T_t, L candidate solutions are generated and tested. Thereafter, the temperature is cooled again by multiplying by a factor α. By choosing a small value for α, it is possible that the system is cooled too fast and the algorithm sticks into a local optimum. Thus, α is normally set to 0.85-0.99.

The stopping criterion can be selected at least in two ways. Either an absolute stopping temperature is used or the optimisation is stopped when the convergence has ended. In this study, it is supposed that an optimal release sequence has been found if the value of the objective function does not change significantly during three consecutive temperatures.

Because of the stochastic nature of the algorithm, the optimisation does not guarantee a global optimum. Therefore, it is a basic procedure to run the algorithm several times with different initial solutions and finally choose the best solution from the ensemble. In other words, instead of allocating all the possible time C to a single walker, it is wiser to run n independent walkers and allocate C/n steps for each of those and choose the best result (Salamon et al., 2002). Again, the decision about the number of parallel runs has to be made by the person supervising the process. The above mentioned three strategies were used to obtain valid initial solutions for the parallel runs in each of the optimisation tasks.

4.1.4.2 Objective function

Regulation rules and the control of a multi-purpose reservoir system are always a compromise between several objectives. The planning of release rules is complicated because there is no commensurable variable available that could be used to evaluate each of the objectives reliably. If the economic value is used, the hydroelectric power benefits are quite easy to approximate, but it is very difficult to approximate recreational and ecological effects and losses caused by floods and droughts financially.

Even so, in this study, the economic value of the regulation is used to determine the value of the inflow forecasts. Some loss functions are subjectively chosen and thus, the final value of the objective function is highly subjective. Hence, also the number of days during which objective water levels, absolute water levels or discharge constrains are violated, is studied. Changes in hydroelectric power production can be approximated economically, however.

In addition to the perfect inflow forecasts, it is also necessary to have perfect knowledge of the future market prices of electricity to make an optimal decision of the releases. In this study, electricity markets are not simulated and thus it is supposed that all generated electricity can be purchased immediately using a given, constant market price.

Objective function in the case study of Lake Pyhäjärvi

It is supposed that all of the electricity generated in the Kauttuankoski power plant can be sold at a price b_i depending on the market price b of the day i. Real market prices are not used. Instead, constant prices are given for the model for summer and winter months: from November to March 30€/MWh and 28 €/MWh in summer. The effects of electricity demand and prices on the quantitative value of the forecasts are not considered here, although Kim and Palmer (1997) have showed that they may significantly affect the value of the forecasts. The head of the plant is set constant (H=10.9 m) and so is its efficiency factor η=0.8. The benefit of hydroelectric power generation during a period of a length d is then

$$Hydro = \sum_{i=1}^{d} \eta \cdot \rho \cdot g \cdot R_i \cdot H \cdot 24 \cdot b_i \; . \qquad \textbf{(4-10)}$$

Here, ρ is the density of water (1000 kg/m^3), g is the acceleration due to gravity (9.81 m/s^2), R_i is the daily release through the turbines (m^3/s), H is the head of the plant (m), 24 is for the 24 hours a day and b_i is the price of electricity (€/MWh). To avoid spill, a cost function is used in the optimisation.

$$Loss_{SPILL} = \sum_{i=1}^{d} \eta \cdot \rho \cdot g \cdot R_{SPILL,i} \cdot H \cdot 24 \cdot b_i \qquad \textbf{(4-11)}$$

where

$$R_{SPILL,i} = \max\left(0; R_i - R_{CAP}\right) \qquad \textbf{(4-12)}$$

is the difference between the maximum capacity (R_{CAP}) of the turbines (6 m^3/s) and the daily release. Thus, the cost is the potential economic value of the daily release that exceeds the capacity of the plant.

Based on the regulation rule of Lake Pyhäjärvi, discharge should be kept above 2.0 m^3/s also during dry seasons and the minimum release limit, 0.8 m^3/s, should never be violated to assure water supply for the downstream plants. Therefore, a cost function was set to minimise the number of days, during which the daily release is less than 2.0 m^3/s. A subjectively chosen cost function was used

$$Loss_{LOW} = \sum_{i=1}^{d} 10^4 \cdot R_{LOW,i} \qquad \textbf{(4-13)}$$

where $R_{LOW,i}$ is the difference between 2 m^3/s and daily release if daily release is less than 2 m^3/s. The absolute minimum release was set to 0.8 m^3/s.

Limits have been set for the upper and lower water levels of Lake Pyhäjärvi in the regulation rule. The lower water level limit is N43+44.54 m and the upper limit is N43+45.12 m throughout the year. In reality, it is permitted to exceed the upper water level limit for short periods of time if it is caused by wind or unusual hydrologic conditions. Each day, when the limits were violated, a cost was calculated using

$$Loss_{WABS,i} = 10^6 \cdot \left|\left(W_{calc,i} - W_{abs}\right)\right| . \qquad \textbf{(4-14)}$$

The large penalty charge guarantees that violations of these limits are avoided at any cost in the release optimisation. Thus, for the upper water level limit violations, the simulated operation is somewhat stricter than the real-world operation. In the operation licence of the lake, some objective water levels are also set. Now, an upper and lower objective level was set for the first and fifteenth day of each month. Most of the objective levels were set subjectively based on the mean observed water levels. The idea was to keep the head of the power plant at least at the height of the observed average or slightly higher. The objectives as well as the absolute water level limits are shown in Figure 30. To obey the objectives a cost was calculated each day when they were violated:

$$Loss_{WOBJ,i} = 100 \cdot \left(100 \cdot \left|W_{calc,i} - W_{obj,i}\right|\right)^3. \qquad \textbf{(4-15)}$$

Between these days, no losses are calculated independent of whether the water levels are inside or outside the objectives. The cubic loss function and the additional multipliers are subjectively chosen. By using this model, the optimisation resulted in water levels that reminded the actual release control policy in the lake. In addition, the benefits of hydropower production were not the only driving force in the optimisation. Water levels are given in meters in Equation 4-14 and in Equation 4-15.

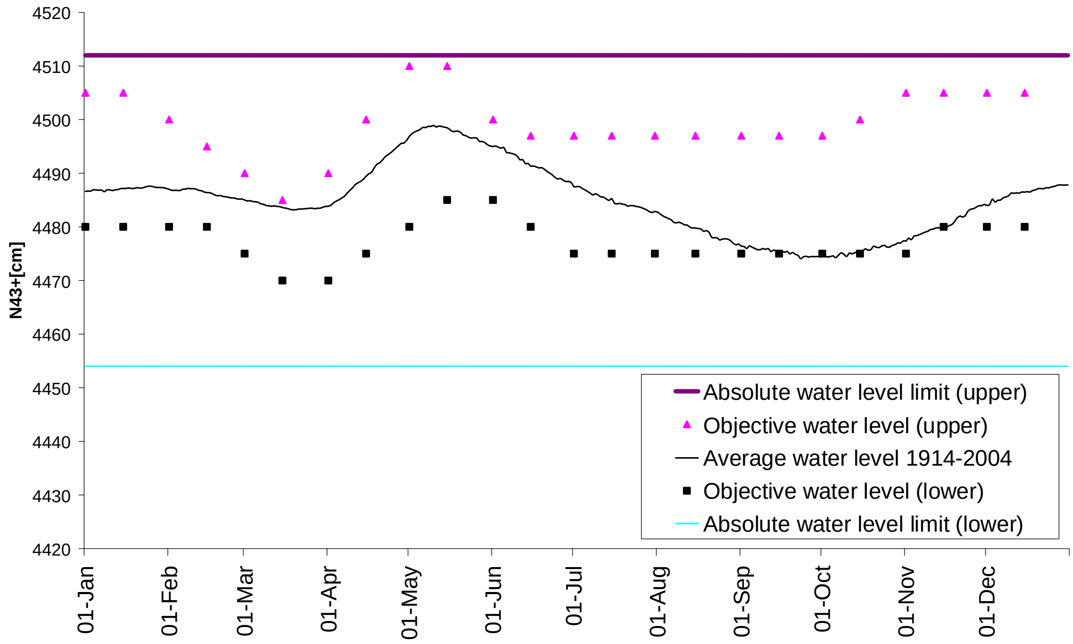


Figure 30. Objective water levels of Lake Pyhäjärvi.

Finally, the objective function of the optimisation algorithm of each forecast period is

$$\begin{aligned} G_{Pyhäjärvi}(R,S,I) = Hydro(R) - Loss_{WABS}(R,S,I) - \\ Loss_{WOBJ}(R,S,I) - Loss_{SPILL}(R) - Loss_{LOW}(R) \end{aligned} \qquad \textbf{(4-16)}$$

As can be seen, no terminal function is set for the state of the reservoir at the end of the forecast period. However, the objective water levels and the relatively short update frequency of the forecasts compared with the forecast length guarantee that the reservoir is not optimised purely based on the maximisation of hydropower production.

Objective function in the Kymijoki case study

The main goals of regulation in the River Kymijoki basin are flood control and effective hydroelectric power production. The value of hydropower production is calculated by using the equation

$$Hydro = \sum_{i=1}^{d} \sum_{j=1}^{12} \eta \cdot \rho \cdot g \cdot R_{i,j} \cdot H_j \cdot 24 \cdot b_i \,, \qquad \textbf{(4-17)}$$

where 12 is the number of the power plants. In Equation 4-17, the price of electricity is not dependent on the market situation. It was assumed that the electricity produced could be sold immediately at a constant price. During the summer months (April-October), the price was set also in this case study to 28 €/MWh and during winters to 30 €/MWh.

Loss functions are defined to avoid possible flood and drought problems and to keep water levels between the objective upper and lower limits. A loss function was also set for spill. An equation similar to Equation 4-17 was used to calculate the financial value of the spillage. As a difference, the term "release through the turbines" $R_{i,j}$ was changed for spill.

$$Loss_{SPILL} = \sum_{i=1}^{d} \sum_{j=1}^{12} \eta \cdot \rho \cdot g \cdot R_{SPILL,i,j} \cdot H_j \cdot 24 \cdot b_i \qquad \textbf{(4-18)}$$

where

$$R_{SPILL,i,j} = \max\left(0; R_{i,j} - R_{CAP,j}\right) \qquad \textbf{(4-19)}$$

and $R_{CAP,j}$ is the capacity of the turbines in power plant j.

The water level limits defined in the operation licenses cannot be violated without a grant of exemption. If fixed absolute water level limits were violated, a penalty was calculated for each day based on the extent of the violations as follows

$$Loss_{WABS,i} = 10^6 \cdot \sum_{k=1}^{4} \left| \left(W_{calc,i,k} - W_{abs,i,k} \right) \right| \qquad \textbf{(4-20)}$$

where k is the index for the lake. The purpose of the large multiplier in (4-20) is to avoid violations in the optimisation process at any cost and thereby to avoid any losses caused by floods and droughts. The loss function for daily violations of the objective water levels is:

$$Loss_{WOBJ,i} = 100 \cdot \sum_{k=1}^{4} \left(\left| W_{calc,i,k} - W_{obj,i,k} \right| \right)^3 \qquad \textbf{(4-21)}$$

In both of these functions water levels are given in centimetres. The objective water levels of Lake Päijänne are presented in Figure 31. Figure 32, Figure 33 and Figure 34 show the objective water levels of Lake Ruotsalainen, Lake Konnivesi and Lake Pyhäjärvi in Iitti, respectively. These water levels are mainly derived from the studies of Järvinen and Marttunen (2000). They investigated ecologically sustainable water levels and discharge changes in the Kymijoki basin in their extensive work (Järvinen and Marttunen, 2000). The objective water levels are defined in the model for the 1st and 15th day of each month. The absolute water level limits are extracted from the operation licenses. However, for Lake Päijänne such limits are not set and thus the water level limits used are subjectively chosen. This is the case also for the lower water level limit in Lake Ruotsalainen.

Based on the operation license of Lake Pyhäjärvi, the absolute upper water level limits of the lake can be exceeded if inflow to the lake is over 400 m^3/s. In the simulation model, no losses corresponding to the absolute upper water level violations were calculated during these kinds of days.

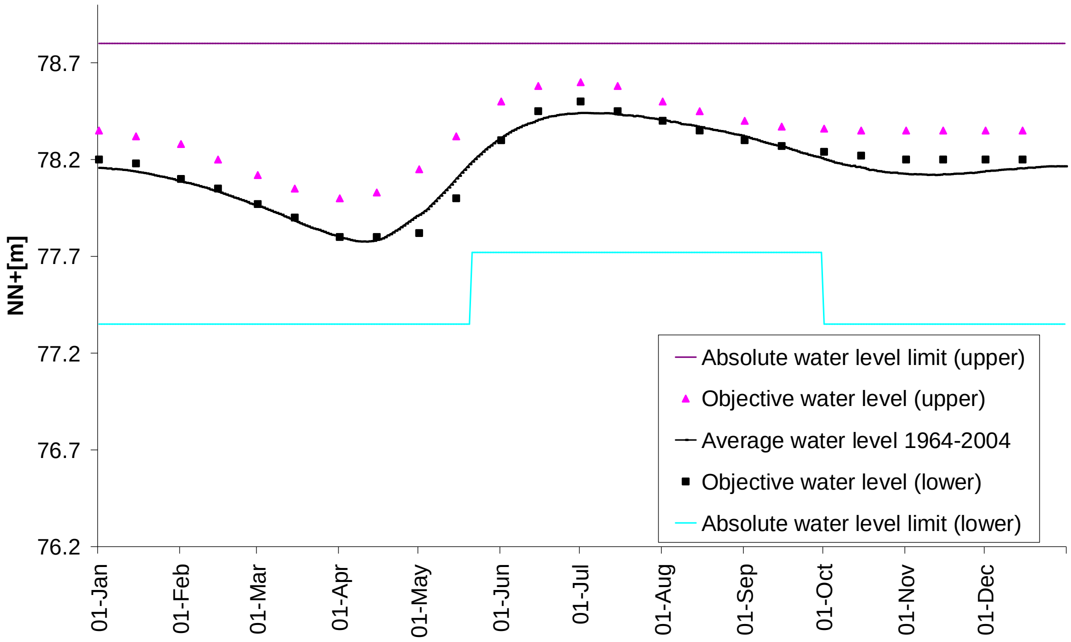


Figure 31. Objective and absolute water levels of Lake Päijänne used in the model. Absolute water level limits are subjectively chosen.

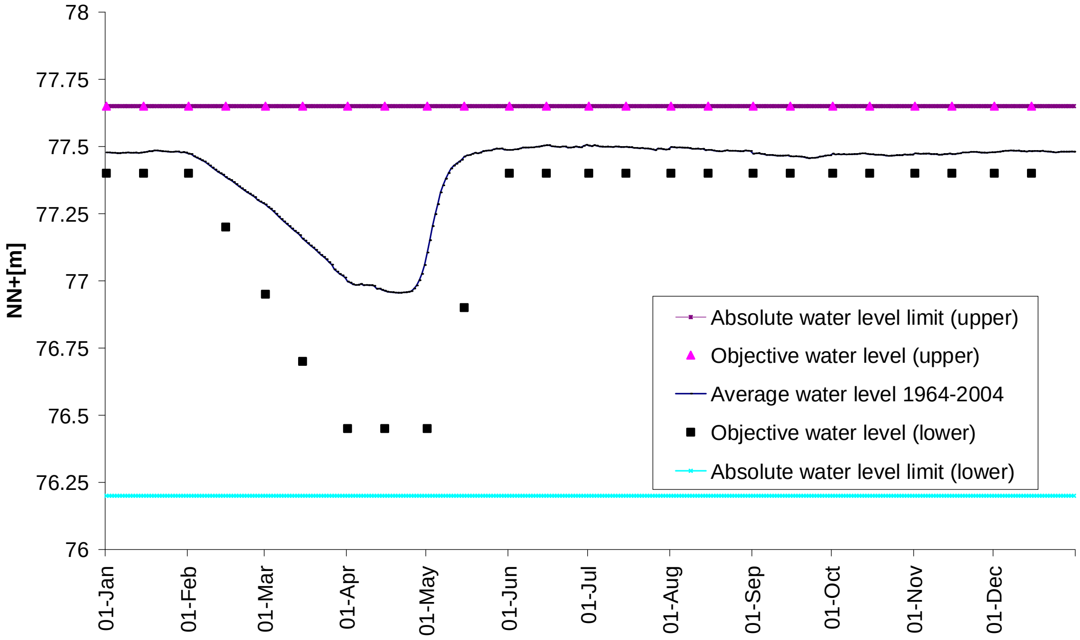


Figure 32. Objective water levels of Lake Ruotsalainen. Lower W_{ABS} are subjectively chosen.

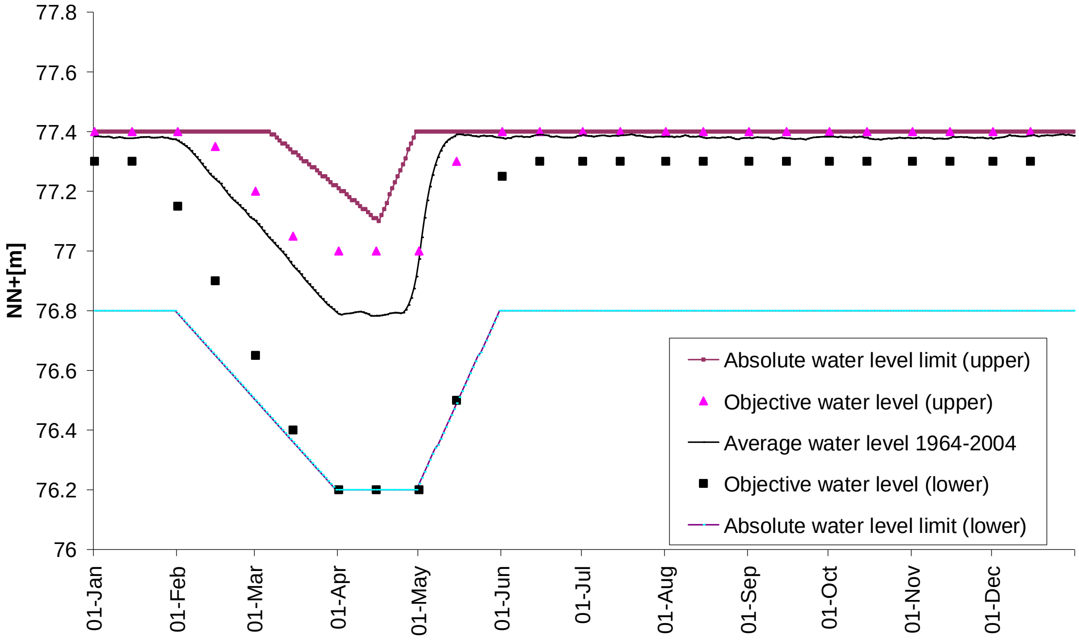


Figure 33. Objective water levels of Lake Konnivesi.

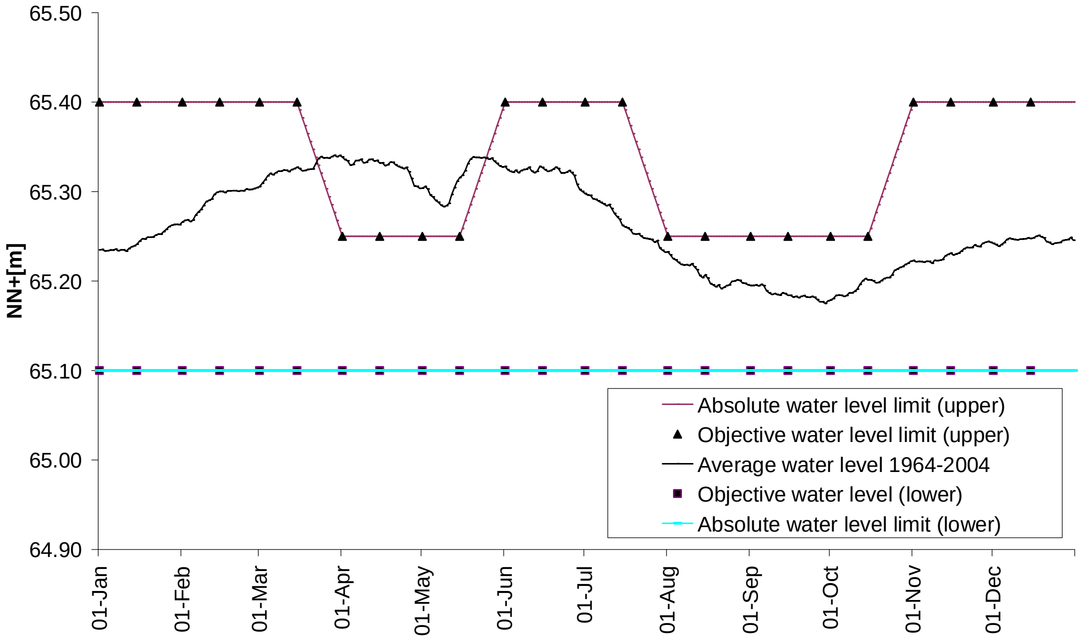


Figure 34. Objective water levels of Lake Pyhäjärvi in Iitti.

Several constraints are set on the releases of different power plants and control weirs. Both minimum and maximum releases are set. In addition, there are some restrictions on discharge changes. These are collected into Table 35.

Table 35. Release restrictions in the River Kymijoki system.

	Minimum release [m^3/s]	Maximum release [m^3/s]	Maximum release change [m^3/s]
Lake Päijänne	50	550	50
Vuolenkoski	50	600	50
Voikkaa	50	700	50

Firstly, the minimum release from Lake Päijänne was set to 50 m^3/s and the maximum was set to 550 m^3/s. In addition, in the regulation licenses the maximum release change during a five days period in Kalkkinen is constricted to 100 m^3/s and to 20-25 m^3/s daily. In the model, this was taken into account by restricting the maximum release change between two consecutive periods of a length of five days to 50 m^3/s. Larger changes may cause some algal problems to fishing nets in Lake Ruotsalainen and Lake Konnivesi located just downstream of Lake Päijänne.

The maximum release of the Vuolenkoski power plant was set to 600 m^3/s and the minimum to 50 m^3/s. Similarly, the maximum release change between two consecutive periods was set to 50 m^3/s. Compared with historical releases, these were hard restrictions, as some changes that are larger than 100 m^3/s have been recorded since 1964.

The maximum release of the Voikkaa power plant was set to 700 m^3/s. The minimum release was set to 50 m^3/s and the maximum release change between two consecutive periods was set to 50 m^3/s. In Voikkaa it is also necessary to keep the minimum release above 150 m^3/s unless some exceptional water conditions occur. At the same time, the maximum should be kept, if possible, below 395 m^3/s. Larger discharges will cause spillage and flood problems downstream and low discharges will harm, for example, the recreational use of the river.

Based on the regulation license of the Kymijoki system and especially Lake Päijänne, discharge in Kuusankoski should be kept above 150 m^3/s. This is mainly due to the recreational use of River Kymijoki but also because of breeding and migration of salmon and other fishes. Therefore, a cost function was set to minimise low discharges downstream of Kuusankoski. A subjectively chosen cost function

$$Loss_{LOW} = \sum_{i=1}^{d} 10^4 \cdot R_{LOW,i} \qquad \textbf{(4-22)}$$

where

$$R_{LOW,i} = \max\left(0;150 - R_i\right) \qquad \textbf{(4-23)}$$

and R_i is daily discharge in Kuusankoski was used. In River Kymijoki, discharges over 400-500 m^3/s cause recreational losses and flood problems downstream. In the optimisation, the avoidance of large releases was taken into account by setting a loss function for spills in different power plants (Equation 4-18). Additional loss functions were not set to minimise large floods downstream. To sum up, the objective function of the optimisation problem is

$$G_{Kymijoki}\left(R\right) = Hydro - Loss_{SPILL} - Loss_{LOW} - Loss_{WABS} - Loss_{WOBJ} \qquad \textbf{(4-24)}$$

4.1.4.3 Selection of a new candidate solution (neighbour)

In the optimisation algorithm, the candidate solution is randomly selected from the "neighbourhood" of the current solution. The definition of a neighbour is a problem specific task and with good choices, it is possible to decrease the computer time needed to find close to optimal or optimal solutions. A neighbour should be defined so that it is possible to move from each state to any other via a reasonable number of steps.

In the release control of Lake Pyhäjärvi in the River Eurajoki basin, a neighbour is defined based on the current solution by increasing or decreasing the release of a single or two randomly selected periods of a length of five days by 0.1 m^3/s. Whether to change the release only in a single period or in two periods is based on a stochastic criterion. If a generated random number (Uni(0,1)) is higher than 0.5, only a single change is made. The possibility to change the releases of two periods ensures that also the timing of the releases is optimal: if the optimal volume has already been found, it is possible to change the timing by increasing the releases in one period and by decreasing the releases in some other period. The neighbourhood of the current solution is restricted to releases that fulfil all release constrains.

In the case study of River Kymijoki, release sequences of three weirs are to be optimised simultaneously. If a forecast period of 30 days is used, six variables in each of the control weirs must be optimised: six for Lake Päijänne, six for Lake Konnivesi (Vuolenkoski) and six for the releases in Lake Pyhäjärvi (Voikkaa). The number increases, of course, if the forecast period gets longer.

In the River Kymijoki reservoir system, a new candidate solution is generated by randomly increasing or decreasing the release (± 5 m^3/s) of none, one or two periods for each of the three control weirs. Hence, it is possible that the new candidate solution differs from the current optimal sequence only slightly. For example, only a single five day release might be decreased (increased), say, in Voikkaa. On the other hand, it is also possible that releases are decreased (increased) for two periods in each of the reservoirs of the system. Of course, the chosen neighbour must fulfil all of the release constraints before it is accepted as a new candidate solution.

4.1.4.4 Parameters

According to Salamon et al. (2002), the initial temperature T_0 can be chosen in a few different ways. In this study, a simple criterion is used and T_0 is set so that about half of the moves downhill are accepted at the beginning of the optimisation. Therefore, the initial value T_0 depends on the scale of the objective function of the problem. However, above all T_0 depends on the sensitivity of the values of the objective function to the selection criteria of a new candidate solution. One of the benefits of approving a big percentage of downhill moves at the beginning of the maximisation is that consequently, the initial states of the parallel runs will certainly be clearly different. In the present study, the algorithm was stopped when the value of the objective function had not improved after three consecutive temperatures.

Because of the third-degree penalty functions (Equations 4-15 and 4-21), the value of the objective function increases quite sharply at the beginning of the algorithm if a poor initial state is used. Thereafter, the climb velocity decreases. This feature made it very difficult to choose the cooling schedule T_t of the algorithm (value of α (Equation 4-8) and L). Parameter values used in the optimisation were set based on test runs.

Computer time used for optimisation was not a problem, if only a single optimisation was considered. Even by using a large *L*, a slow cooling schedule and a long optimisation period (many variables), the computer time of a single optimisation was a matter of seconds. However, to maintain a reasonable time in overall computation (parallel runs, different tasks), it was necessary to aim at good close to optimal solutions in the shortest possible time. In Table 36 the parameters used in the case study of Lake Pyhäjärvi are given. The sensitivity of the results to parameter selection is discussed in Chapter 4.4. Five parallel runs were used in each of the optimisation problems.

Table 36. Parameters used in the optimisation of the releases in Lake Pyhäjärvi.

Forecast length	Update interval	Variables	α	L
30	15	6	0.90	50
60	15	12	0.90	50
90	15	18	0.90	50
120	15	24	0.90	100
150	15	30	0.90	100
180	15	36	0.90	100
270	15	54	0.90	100
360	15	72	0.90	200

The optimisation of the four reservoir systems of the River Kymijoki system including three control weirs is a much more complicated task than optimisation of a single reservoir system. At each of the optimisation tasks, three parallel runs with different initial states were made and the best result of the ensemble was selected. Especially when using a randomly selected initial state, the value of the objective function increases rapidly at the beginning of the optimisation. Therefore, it was difficult to find a proper cooling schedule for the problem. In the case study of River Kymijoki, the exponential cooling schedule was modified slightly. In the beginning the value of α was set to 0.5. This guaranteed fast cooling while the value of the objective function was increasing rapidly. The value of α was increased, however, while cooling down the temperature by a step 0.02 until it reached the chosen maximum value (Table 37). Therefore, the cooling velocity was faster at the beginning of the optimisation (α = 0.50) compared to the cooling velocity at later stages. In Table 37, the parameter values used in the optimisation are given. In the case study of River Kymijoki the longest forecast period studied was 120 days.

Table 37. Parameters used in the optimisation of the releases in the River Kymijoki basin.

Forecast length	Update interval	Variables	Max α	L
30	15	18	0.90	200
60	15	36	0.90	300
90	15	54	0.90	400
120	15	72	0.90	400

4.2 Results for the case of Lake Pyhäjärvi

4.2.1 Perfect inflow forecasts

A period of simulated water levels in Lake Pyhäjärvi and the corresponding releases in the outlet are presented in Figure 35. The simulation was based on the utilisation of perfect inflow forecasts (σ=0.0) of a time period of three months (90 days). Forecasts were updated every 15 days. The observed values are also shown for comparison.

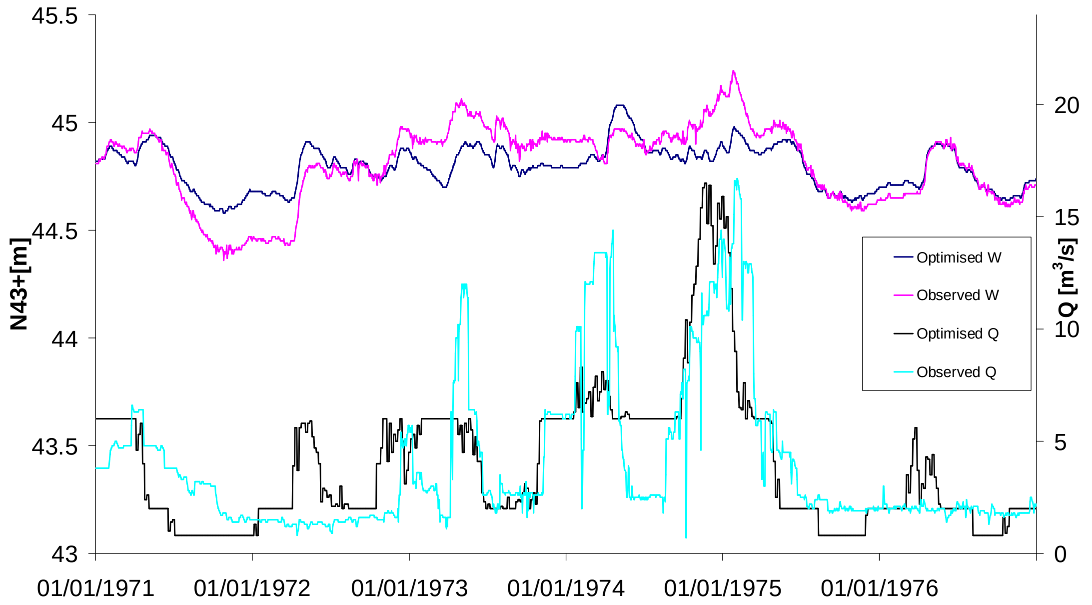


Figure 35. Observed release sequence during 1971-1976 and optimised release sequence attained by using perfect forecasts of a lead-time of 90 days. Water levels are also shown.

Two important phenomena that are valid throughout the whole simulation period (1967-2004) can be seen. Firstly, both the extent of spill and the number of days during which the maximum release capacity (6.0 m^3/s) is exceeded, have decreased compared to observations in the case where perfect inflow forecasts were used. Secondly, Lake Pyhäjärvi could have been operated through the whole simulation period without violating the upper and lower water level limits set in the regulation licenses (N43+44.54 m and N43+45.12 m). In historical records these limits were violated during 813 days, partly because of the possibility to violate the upper limit during unusual hydrologic conditions. In addition, the variation of both the releases and the water level has decreased and the release sequence is smoother. The average water level in the simulation was N43+44.83 meters while it was only one centimetre higher in real-life based on the observations during the same period.

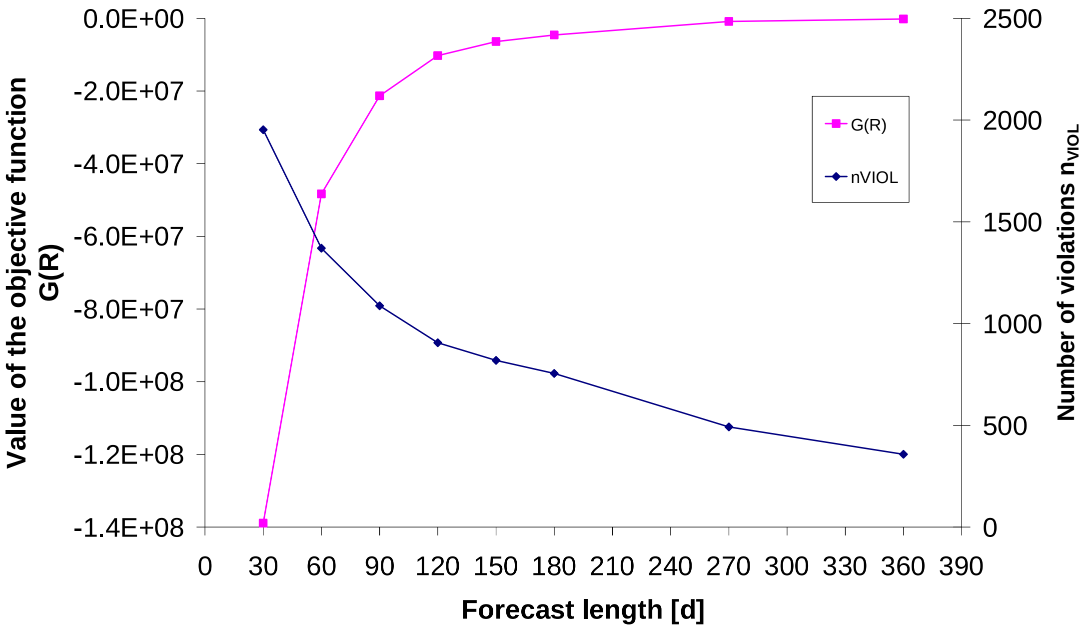


Figure 36. Dependence of the value of perfect forecasts on forecast length in Lake Pyhäjärvi. Simulation of years 1967-2004.

When using perfect inflow forecasts the operation of the system improves as the forecast period gets longer (Figure 36). This is true up to the longest period studied. At first the improvement is rapid but steadies to modest as the forecast length exceeds 5-6 months. Some of the objective water levels and loss functions were subjectively chosen. Thus, instead of analysing the value of the objective function *G(R)*, it is more valuable to study how often the objective and absolute water levels and the objective minimum release (2.0 m^3/s) are violated. In addition, it is important to study the effect of availability of longer forecasts on hydropower.

Figure 36 shows that the total number of violations (n_{VIOL}) decreases as the forecast period gets longer. When using perfect inflow forecasts of a time period of one month in the operation of the reservoir, the fixed absolute upper and lower water level limits of the lake were violated on 438 days (n_{WABSU} and n_{WABSL} in Table 38). When using forecasts of a length of 60 days these limits were violated only on 12 days. When using longer, perfect forecasts, the absolute water level limits were not broken at all. The number of violations of the objective water levels (n_{WOBJ}) can be decreased by over a half if the forecast period is lengthened from 30 days to periods exceeding three months. At the same time, also the number of days during which objective minimum release is violated (n_Q) decreases rapidly. It decreases from 990 days by using a forecast period of a length of one month to 146 days by using forecasts of a length of 360 days. Because the regulation did not begin until 1975 and the goals of the regulation may have been different during different seasons, it is not worthwhile to compare these figures with the observed values.

The additional benefit gained from the use of longer inflow forecasts decreases significantly when the forecast length of 5-6 months is exceeded. After that the increase in the value of the objective function and the decrease in n_{VIOL} (the total number of violations) are almost entirely caused by the ability to avoid more efficiently the releases that violate the release limit, 2.0 m^3/s. For example, the n_{WOBJ}

decreases only from 239 to 212 while lengthening the forecast period from 120 days to 360 days (see Table 38).

Table 38. Number of violations concerning water levels and outflows in Lake Pyhäjärvi by using perfect inflow forecasts of different lengths.

Length of the forecast [d]	n_{WABSL}	n_{WABSU}	n_{Q}	n_{WOBJ}
30	408	30	990	524
60	12	0	1013	345
90	0	0	823	264
120	0	0	667	239
150	0	0	595	224
180	0	0	538	217
270	0	0	275	217
360	0	0	146	212

Hydropower production in the Kauttuankoski power plant would have increased significantly if perfect forecasts had been available. Compared with the value of hydropower by using the observed releases, 2 530 000 €, the value would have been larger, about 2 780 000 €, if perfect forecasts of a time period of 12 months had been available. The comparison was made only for the period of regulation (1975-2004). The value of hydropower production would have increased about 9% and by using the set constant prices, 8450 € per year. This was mainly due to the decreased spillage in the Kauttuankoski plant. The effect of lengthening the forecast period on hydropower production is shown in Figure 37 for the period 1967-2004. Hydropower production benefits from short forecasts at the expense of acceptable water levels as terminal function was not set. If longer forecasts are used (2-3 months), the water level of the lake begins to dominate the objective function more at the expense of hydropower production. If the forecast period is lengthened up to a year, it is possible to gain almost the same benefit as by using the forecasts of 30 days, but at the same time avoid most of the problems related to water levels. However, the differences in hydropower production between the different forecast lengths are small, less than 1%. In addition, one should bear in mind that results are partly dependent on the chosen loss functions.

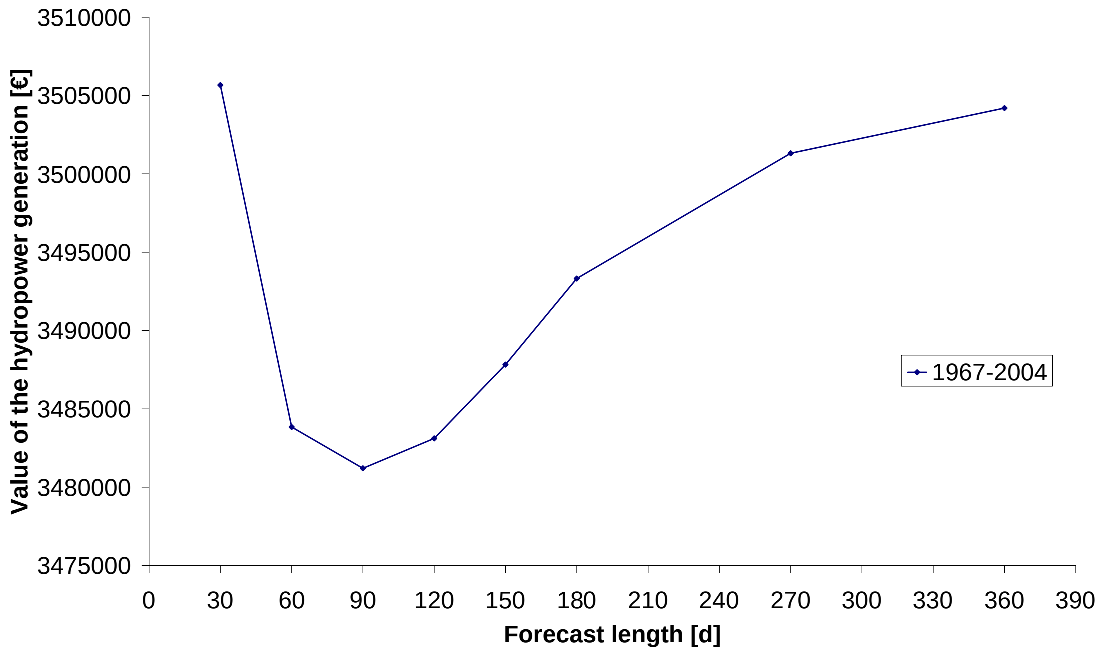


Figure 37. Value of hydroelectric power production as a function of forecast length (perfect forecasts) in Lake Pyhäjärvi for period 1967-2004.

4.2.2 Inaccurate inflow forecasts

The operation of Lake Pyhäjärvi was simulated (1967-2004) by using the average of the historical inflows of three and four months as forecasts. In addition, the lake was operated through the simulation period by using inaccurate artificial inflow forecasts. The artificial forecasts were generated by using the Equation 4-2 with different values of σ. Also the effect of autocorrelation between the forecast errors was analysed. The values of the objective function as a function of forecast length and accuracy are shown in Figure 38.

The extension of inflow forecasts up to a period of five to six months improves the operation of the lake even if the forecasts are poor (σ=1.0). Despite the large errors, the inflow forecasts contain much valuable information because of the unbiased model. If forecast errors are small and forecasts are updated regularly, the value of the forecast increases with the forecast length up to a year's period. Generally, the less accurate the forecasts, the shorter the longest reasonable forecast period. For σ=0.1 it was at least a year, for σ=0.3 at least nine months, for σ=0.5 about six months and for σ=1.0 about five months. Because of the uncertainties related to the random number ε in the Equation 4-2, and the subjectively chosen cost functions, these figures are only suggestive. The additional autocorrelation between the forecast errors makes these periods slightly shorter. For small values of σ, the effect of the autocorrelation is very small, however. If σ=0.1 or σ=0.3 the change in the value of the inflow forecasts caused by the additional autocorrelation (a_1=0.80) is not statistically significant compared with the case where a_1=0. If σ=1.0, the additional autocorrelation (a_1=0.8) in the forecasts will cause serious problems in the operation of the lake. These problems were not dependent on the forecast length.

Up to a certain forecast length and up to a certain σ, it is valuable to use longer forecasts although forecast accuracy would simultaneously decrease. Thus, at least a forecast length of two months should be used in the operation of Lake Pyhäjärvi. For example, it is better to use the average historical inflow of a time period of 90 to 120 days as a forecast instead of the perfect forecasts of a time period of 30 days. Depending on forecast accuracy, at some point the additional value of the longer forecasts is lost, however. Generally, it seems that it is not worthwhile to use forecast periods exceeding 120 days in Lake Pyhäjärvi if the forecast accuracy weakens significantly at the same time. For example, it is more worthwhile to use forecasts of 120 days with σ=0.1 or σ=0.3 than forecasts of 150 days or longer with σ=0.5. The differences are statistically significant. If errors are larger, this forecast period is shorter. Although the differences in the values of the objective function are not statistically significant (confidence limit 0.05) at every pairwise comparison, the variance of the value of the objective function also increases with increasing σ. In addition, on average, the absolute water level limits and the release restrictions are violated more often.

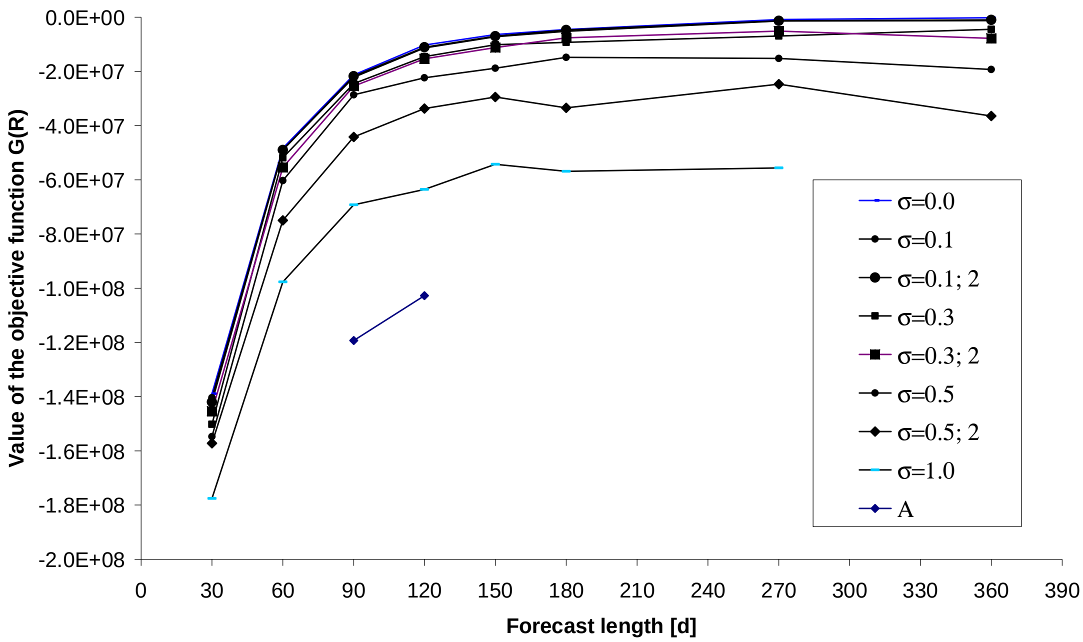


Figure 38. Value of the objective function as a function of forecast length and accuracy in Lake Pyhäjärvi. Index 2 indicates that consecutive forecast errors were a_1=0.8 autocorrelated. A = average historical inflow as a forecast.

These results can also be studied in the light of hydropower production, water levels and releases. The results are compared with the outcome of the lake operation where the perfect inflow forecasts of a time period of 12 months were utilised. So, it is possible to analyse the extent to which the inaccurate forecasts and shorter forecasts cause problems and decrease the potential hydropower production and its financial value. In Appendix G, the number of days during which the different violations occurred are presented for the different forecast accuracies and forecast periods.

If a forecast length of three months or longer is used, it is possible to avoid violations of the fixed, absolute, lower water level limits in Lake Pyhäjärvi, although inflow forecasts would contain small errors. At the same time, only occasional single violations of the upper limits are recorded. For shorter periods, the number of violations is large even if perfect forecast are used.

The objective water levels are violated although perfect forecasts are used. The number (n_{WOBJ}) is not affected as small errors occur, but increases (uniformly) as the forecast accuracy continues to weaken. The decrease in accuracy also significantly increases the number of the minimum release violations (n_Q). The overall number of the violations is a multiple of the chosen base point both if the forecast length is short and if forecast errors are large.

Figure 39 shows the effect of the forecast length and accuracy on the value of hydroelectric power production. Compared with the simulation using perfect forecast of a length of 360 days, it is possible to lose up to 0.7% of the financial value of hydropower by just using too short inflow forecasts in the operation. Financially, this is not more than 600 €/a year in Lake Pyhäjärvi, but as already seen, “losses” are larger if the water level and the release restrictions are taken into account.

By combining short forecasts with forecast inaccuracy, the financial loss percentage can be over 10% (over 10000 €/a). A small random error (σ = 0.1) in the forecasts decreases the annual benefit of hydroelectric power production only by 0.2-1.4%. If it were possible to increase forecast accuracy from σ = 0.3 to σ = 0.1, hydroelectric power production would benefit by 1-3% depending on the forecast length.

The autocorrelation (a_1=0.80) between the forecast errors has no significant effect on the value of hydroelectric power production compared with the case where a_1=0. By using the historical average as an inflow forecast, the losses are concentrated on the unwanted flood and drought problems instead of large losses related to hydropower production. By using the historical average of a time period of three months as a forecast, the simulated losses in hydropower production are no more than 3.1% of the optimal value. For the chosen prices, it is only 2800 € per year.

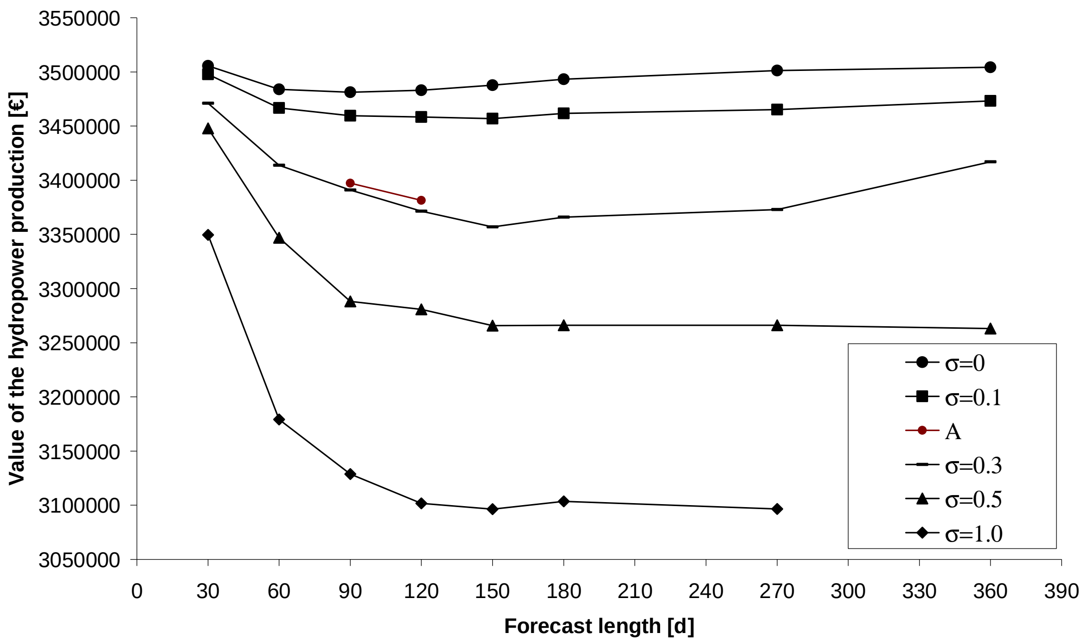


Figure 39. Dependence between the value of hydroelectric power production and forecast error and length in Lake Pyhäjärvi. The results by using the mean historical inflow as a forecast are marked with the symbol A.

The sequence of the random number ε in the Equation 4-2 causes a stochastic effect on the results. A large random error on some occasion may have larger effects on the operation of the lake than an equal error on some other occasion. Therefore, the whole period was simulated 15 times. The variances of the results between the independent runs (15 times 1967-2004) for each value of σ were not presented above. For each simulation, a different forecast error sequence was attained and as a consequence, the value of the objective function for the whole period 1967-2004 was different. Fifteen independent runs do not guarantee, naturally, that the worst (and best) case scenario would be studied but they do give an idea about the possible consequences of the forecast errors on the operation of the lake. An analysis of the standard deviations of the studied variables in the case study of Lake Pyhäjärvi is given in Table 39. Forecasts of a length of 90 days with σ=0.3 are used as an example. The whole period 1967-2004 was simulated 15 times by updating the forecasts every 15 days. The results of the runs for which the objective function obtained its minimum and maximum values are given.

Table 39. The results of the simulations of the period 1967-2004 when using forecasts of a lead-time of 90 days and σ=0.3 in Lake Pyhäjärvi. Results of the runs for which the objective function obtained its minimum and maximum values are given. Average values and standard deviations of the 15 parallel runs are also given.

	G(R)	Hydropower value [€]	n_{WABSL}	n_{WABSU}	n_Q	n_{WOBJ}	n_{VIOL}
Min	**-27899566**	3404115	0	7	1020	275	1302
Average	**-24484409**	3391034	0	7	957	266	1231
Max	**-22023200**	3385885	0	6	880	271	1157
St.dev	**1718056**	16356	0	6	79	10	81

As demonstrated, the value of the objective function varied from -14% to +10% around the average value. The differences in the number of violations of the absolute upper and lower and objective water level limits are relatively small. The number of violations of low releases, however, varied between 880 and 1020. Generally, the larger the error (σ), the larger the standard deviations.

4.2.3 Update frequency of the forecasts

The update frequency of the forecasts affects the results. The longer the update frequency, the worse is the operation of the system even in the case where perfect forecasts are available. The differences in the results are accentuated if the forecast model is inaccurate. In real time forecasting and operation of a system, forecasts and observed inflows are compared and evaluated daily. If values differ significantly, forecasts and/or the planned operation of the system is updated. Thus, it is unlikely that a reservoir or a reservoir system is operated by using poor forecasts for a very long period. To study the dependence between the update frequency of the forecasts and the value of the forecasts, the operation of the Lake Pyhäjärvi system was simulated using three different update frequencies (5, 15 and 30 days). The system was operated both using perfect forecasts and using different values of σ. The results corresponding to the perfect inflow forecasts are shown in Figure 40. The system was operated in each case from 1967 until the end of 2004. As before, the average values of 15 independent runs are presented.

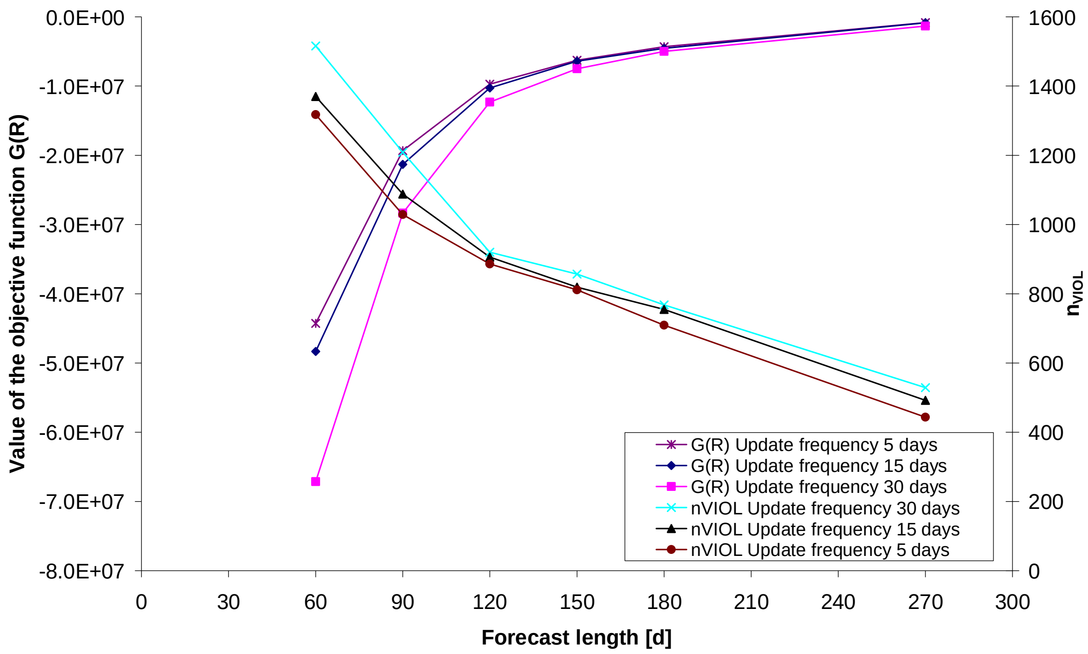


Figure 40. Dependence between the value of the forecasts and their update frequency by using perfect inflow forecasts in Lake Pyhäjärvi.

The longer the update frequency, the worse the system can be operated. This is true especially if long update frequencies are used compared with the forecast length. Differences are small if the forecast period is long. When a forecast period of 60 days and perfect forecasts were used, the number of days during which the lower absolute water level limit was exceeded, increased from 11 to 12 and again to 49 days, when the update frequency was lengthened from 5 first to 15 days and again to 30 days. At the same time, both the number of days during which the release in the Kauttuankoski dam was less than 2.0 m^3/s and the number of days during which the objective water levels were violated increased. The results were similar when a forecast period of 90 days was used, although the absolute water level limits were not violated in any of the simulations. When using perfect inflow forecasts, the effect of the update frequency on hydropower production was insignificant. The longer the forecast length is compared with update frequency, the less significant is the update frequency of the forecasts in reservoir operation.

For inaccurate forecasts, the results are similar. If errors are small, the success of the regulation will decrease if short forecasts and a long update frequency are used. For longer forecast periods, differences are insignificant. For larger errors, the update frequency is in a more significant role. For σ=0.5, it is possible to lose 1-2% of hydroelectric power production and increase the number of violations up to 20% if the update frequency of the forecasts is changed from 15 days to 30 days.

4.2.4 Confidence limits of the inflow forecasts

All of the preceding results were based on the assumption that the system is operated based on the mean forecast; see Equations 4-4 and 4-5. Thus, the confidence limits of the forecast were not used and the optimisation problem was a deterministic one. To study the effect of solving a stochastic problem (Equation 4-4) instead of the deterministic problem (Equation 4-5), the optimisation problem was updated and all the calculations were re-run. The main results are shown in Figure 41 and Figure 42.

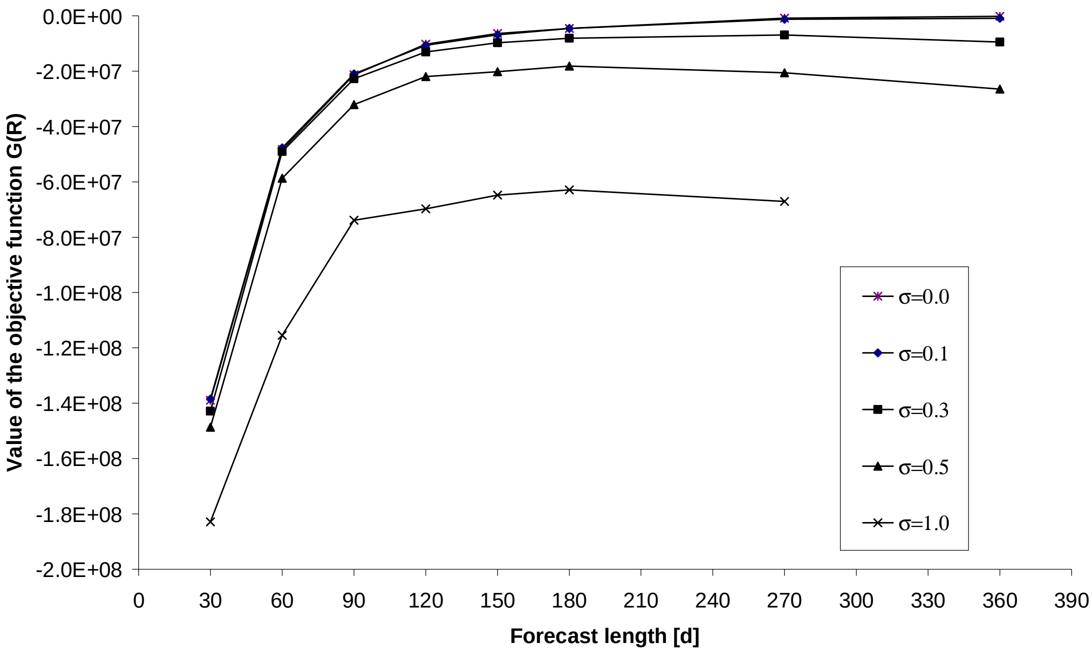


Figure 41. The value of the objective function as a function of forecast length and accuracy by using stochastic optimisation in Lake Pyhäjärvi.

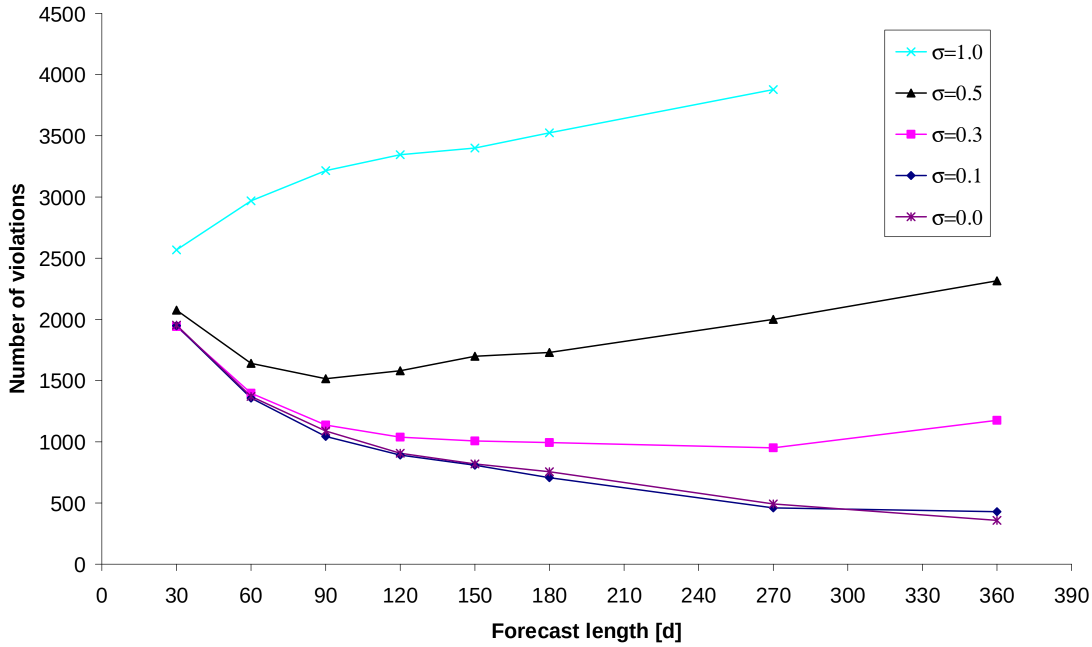


Figure 42. Number of violations as a function of forecast length and accuracy by using stochastic optimisation in Lake Pyhäjärvi.

If the confidence limits are taken into account, the value of the objective function improves compared with the results of the deterministic optimisation. This is true if forecast errors are decent. If very poor forecasts are used ($\sigma \geq 0.5$), it is better to solve the deterministic problem. This is due to the loss functions of the problem. The overall value of the objective function decreases because of the unnecessarily large usage of releases that are below the release limit 2 m^3/s.

The additional value of the longer forecasts is small if the 5-6-month forecast period is exceeded. If, however, errors are small (σ=0.1), it is reasonable to use a forecast period of a length of up to 9 months ahead. If errors are larger and if errors do not increase as the forecast period lengthens, the optimal forecast length is about 5-6 months. The additional value of the forecasts is lost, however, if the accuracy decreases at the same time. For example, it is better to use forecasts of a length of 4 months with the accuracy of σ=0.1 than those of 5 months with the accuracy of σ=0.3. For poor forecast, it is not reasonable to lengthen the forecast period from 3-4 months if forecast accuracy decreases significantly at the same time.

Hydropower production will decrease if the confidence limits are utilised. This is due to large costs associated with the absolute water level limit violations. Although the probability of over- or underestimating the inflow volume and thus the probability of violating the water level limits is very small, the high costs of the violations force into non-optimal releases with respect to hydropower production. The effect of utilising the confidence limits of the forecasts on hydropower production is dependent on the forecast length and accuracy. Generally, the production decreases from 0.1 up to 9% compared with the use of the deterministic optimisation. At the same time, however, the total number of the violations decreased by up to 10% if σ is 0.1 or 0.3. For larger σ, the increasing number of n_Q causes an increase in n_{VIOL} and a decrease in the value of $G(R, S, I)$. If hydroelectric power production is compared with the results of the simulation using perfect forecasts of a time period of 360 days, the decrease in the production is from 1% up to 18% depending on the accuracy and length of the forecasts. Again, one should bear in mind that results are dependent on the chosen subjective cost-functions.

4.3 Results for the case of River Kymijoki

The value of the inflow forecasts in the River Kymijoki basin was studied. All the lateral inflows downstream of Lake Päijänne were based on water balance studies and were accurate. Therefore, the study is about the dependence between the inflow forecasts to Lake Päijänne and the operation of the lake-river system supposing that all the forthcoming, lateral inflows are perfectly known.

4.3.1 Perfect inflow forecasts

Firstly, the operation of the Kymijoki lake-river system was studied in the case where the accurate inflows to Lake Päijänne were used as forecasts. Different forecast lengths were studied. The update frequency of the forecasts was 15 days. As an example, a seven-year season of water levels simulated by using perfect inflows of a time period of 90 days as forecasts is shown in Figure 43. Some important facts can be seen. Firstly, the annual maximum water level of Lake Päijänne does not rise as high as the maximum of the observed values. The averages of the simulated and observed water levels of Lake Päijänne, however, are about the same. Thus, water level changes have smoothed.

Secondly, because of the more effective use of live capacities of the lakes, the average water levels of Lake Ruotsalainen and Lake Konnivesi in the simulation are less than the averages of the observed values. Water levels of the lakes are close to the fixed minimum water level limits before spring floods. Thus, for the benefit of the whole system, the spring drawdown in Lake Ruotsalainen and Lake Konnivesi should have been larger in history. At the same time, Lake Pyhäjärvi could have been operated in such a way that its water level would not have exceeded the upper water level limits as often. Also the maximum water levels have fallen. Thus, the simulated average is below the mean of the observed values in Lake Pyhäjärvi.

The averages of the simulated water levels are shown in Table 40 and the average observation-based water levels were shown already in Table 1 (page 33). The simulated maximum and minimum water levels during the operation period 1965-2004 only slightly approach each other when the forecast period gets longer. By using the live capacities of the lakes efficiently, some of the flood peaks downstream of Lake Pyhäjärvi during the simulation period 1965-2004 decreased. This effect was small, however.

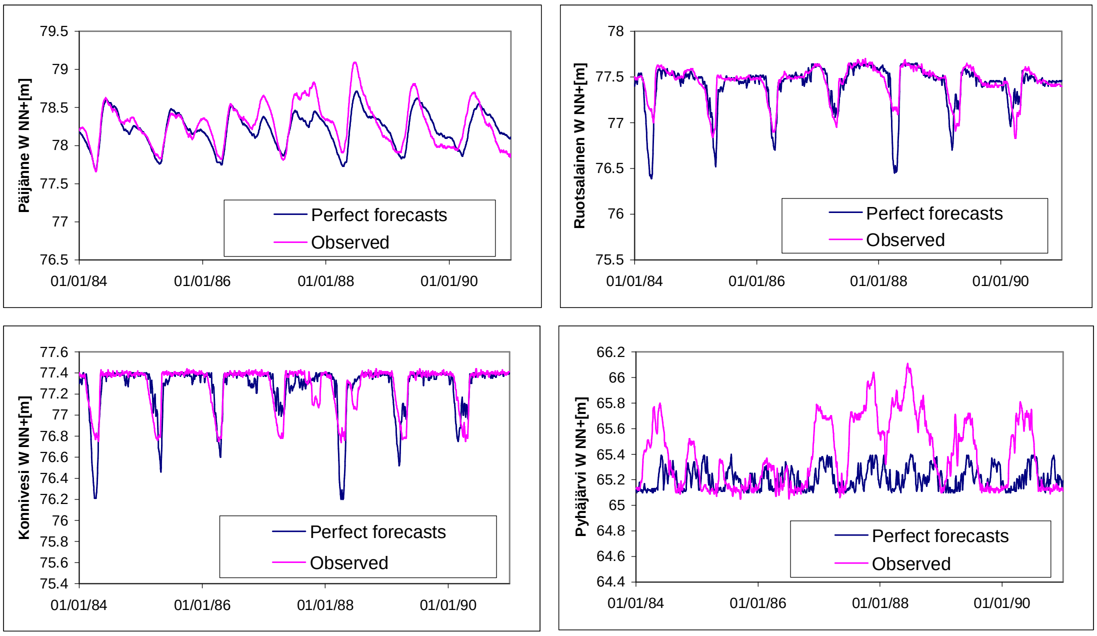


Figure 43. Simulated water levels in the River Kymijoki system during 1984-1990 when the system was operated by using perfect forecasts of a lead-time of 90 days.

Table 40. The simulated maximum and minimum water levels in the lakes in the River Kymijoki system during 1965-2004 when the system was operated by using perfect inflow forecasts; see also Table 1.

	Päijänne			Ruotsalainen		
Forecast Length	Wmax [NN+m]	Average [NN+m]	Wmin [NN+m]	Wmax [NN+m]	Average [NN+m]	Wmin [NN+m]
30	78.76	78.08	77.36	77.65	77.27	76.27
60	78.69	78.15	77.48	77.65	77.36	76.29
90	78.71	78.18	77.53	77.65	77.39	76.34
120	78.71	78.19	77.57	77.65	77.39	76.32

	Konnivesi			Pyhäjärvi		
Forecast Length	Wmax [NN+m]	Average [NN+m]	Wmin [NN+m]	Wmax [NN+m]	Average [NN+m]	Wmin [NN+m]
30	77.40	77.14	76.20	65.58	65.15	65.10
60	77.40	77.23	76.20	65.55	65.18	65.10
90	77.40	77.26	76.20	65.52	65.19	65.10
120	77.40	77.27	76.20	65.62	65.20	65.10

The value of the objective function increases as the forecast period becomes longer, but only until the forecast length of three months is used (see σ=0.0 in Figure 44). The perfect forecasts of a length of three months contain most of the relevant information needed in the optimal operation of the lake-river system. The additional value of the longer forecasts is small. In fact, already the additional value of using forecasts of a length of 90 days instead of forecasts of a length of 60 days is relatively small.

The additional value of the longer, perfect forecasts can be seen in the decreasing number of the days during which the objective and the absolute water level limits are violated (Table 41). By lengthening the forecast period, it is possible to decrease the number of violations of the objective water level limits to two-thirds in Lake Päijänne and in Lake Konnivesi and to one-fifth in Lake Ruotsalainen. In Lake Pyhäjärvi this effect is small, however. The overall number of the violations of the objective water level limits remains large. The large number is a consequence of small losses caused by small violations: most of the violations are in the order of magnitude of only a few centimetres.

The violations of the absolute water level limits could be practically avoided by using the shortest forecast period of one month, with the exception of Lake Pyhäjärvi in Iitti. The large number of absolute water level violations in Lake Pyhäjärvi is a consequence of the small live capacity of the lake compared with its average inflow. Notice that the violations of the fixed water level limits are permitted in the operation licenses if the lake's inflow is large.

Table 41. Violations of water level limits (1965-2004) in the River Kymijoki system when perfect forecasts were utilised.

	Päijänne		Ruotsalainen		Konnivesi		Pyhäjärvi	
Forecast length	n_{WABS}	n_{WOBJ}	n_{WABS}	n_{WOBJ}	n_{WABS}	n_{WOBJ}	n_{WABS}	n_{WOBJ}
30	2	914	2	462	0	317	141	17
60	0	741	1	137	0	203	147	20
90	0	627	0	78	0	202	152	26
120	0	636	0	73	0	209	125	25

Two things can be seen immediately when the value of the perfect forecasts on the hydroelectric power production is studied. Firstly, by using longer forecasts, spillage can be decreased and the overall production increased. It is also possible to benefit more from higher prices during wintertime. However, the effect is small. Compared with hydroelectric power production simulated using the observed releases, the increase in power production resulting from the use of perfect inflow forecasts of four months is around 9.5 GWh (0.7%) annually (Table 42). The small increase in the production may be financially considerable, however. If this is viewed as an annual financial benefit, it would increase the income of the power companies by about 282 000 € per year if constant prices are used. An important part of this increase is due to a more efficient utilisation of the live capacities of Lake Konnivesi and Lake Ruotsalainen (spring drawdown).

Table 42. The effect of forecast length on hydroelectric power production in the River Kymijoki basin by using perfect forecasts compared to the case of using observed releases in 1965-2004.

Forecast length	Increase compared to observed releases 1965-2004 (51249415 MWh, 1 477 772 065 €).			
[d]	MWh [%]	€ [%]	MWh/a	€ /a
Observed	0.0	0.0	0	0
30	0.0	-0.1	-2100	-32000
60	0.4	0.4	4700	163000
90	0.6	0.7	8000	252000
120	0.7	0.8	9500	282000

4.3.2 Inaccurate inflow forecasts

The system was also operated using the daily historical inflow averages as forecasts. In addition, artificial random errors were added to the perfect forecasts by using different values of σ in the Equation 4-2 and by adding autocorrelation between the consecutive errors (Equation 4-3).

To take into account the contingency of the errors and their timing, the simulation period was run through 15 times and the averages of the results of these simulations were studied. The update frequency of the forecasts was 15 days. The value of the objective function of the period 1965-2004 for the forecasts of different lengths and different values of σ are given in Figure 44. To narrow the scale in the figure, poor results corresponding to the use of the historical averages and forecasts of accuracy of σ=0.5 as forecasts are not shown.

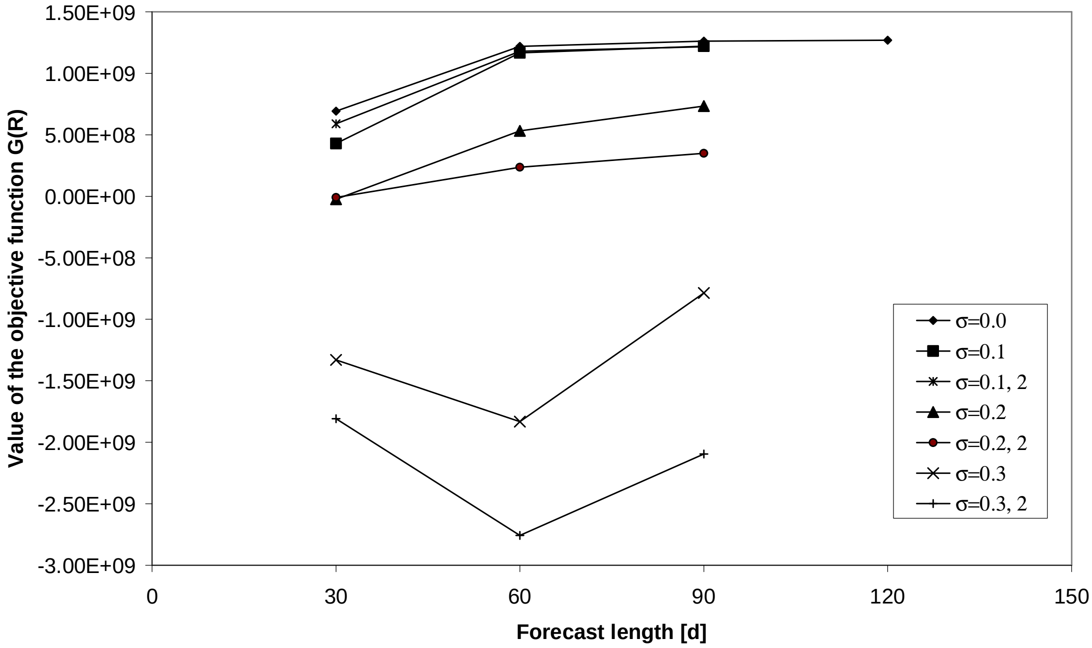


Figure 44. The value of the objective function as a function of forecast length and accuracy in the River Kymijoki system. Index 2 is used for a_1=0.8. Simulation period 1965-2004.

If errors are small (σ=0.1), the value of the objective function is only slightly less compared to the case of the perfect forecasts (σ=0.0). However, the increase in the errors to σ=0.2 and to σ=0.3 evidently decreases the value of the forecasts. In addition, it was discovered that if σ=0.5, forecasts were so weak that the success of the operation of the lake-river system based on these forecasts was poor.

If forecast accuracy does not decrease, it is worthwhile to lengthen the forecast period up to 90 days in cases where the errors are small (σ=0.1 or σ=0.2). For the less accurate forecasts, the effects are less obvious. If forecast accuracy decreases significantly (e.g. from σ=0.1 to σ=0.2) as the forecast period lengthens, it is better to use shorter forecasts. Generally, the relatively small additional value of the longer forecasts is lost if forecast errors increase as function of the forecast lead time. The additional autocorrelation will increase the losses caused by the inaccurate forecasts. This negative effect on the overall operation of the system increases with increasing σ.

The drop in the value of the objective function as a consequence of inaccurate forecasts is mainly caused by the inability to avoid the fixed water level limits (Table 43). Inaccurate forecasts can increase the total number of water level violations in the four lakes studied by over 50%. This is the case when using 60-day forecasts and increasing the error from σ=0.0 to 0.5. For the individual lakes, this increase can be much larger. For example, in Lake Päijänne the number of violations of the fixed absolute water level limits increased from 2 to 158 while σ increased from 0.0 to 0.5 and the forecast period of 30 days was considered. Generally, Lake Päijänne is the most vulnerable to forecast errors if measured based on the violations of the water level limits.

The decrease in forecast accuracy also affects the operation of Lake Ruotsalainen and Lake Konnivesi. The less accurate the forecasts are, the more violations occur. However, these lakes are not as sensitive to forecast accuracy as Lake Päijänne.

Table 43. The dependence between forecast length and accuracy and the number of fixed water level limits violations in Lake Päijänne and the downstream lakes.

Forecast length and accuracy	n_{WABS} Päij.	n_{WOBJ} Päij.	n_{WABS} Ruots.	n_{WOBJ} Ruots.	n_{WABS} Konni.	n_{WOBJ} Konni.	n_{WABS} Pyhäj.	n_{WOBJ} Pyhäj.
30, σ=0.0	2	914	2	462	0	317	141	17
30, σ=0.1	29	897	5	447	0	306	124	16
30, σ=0.2	42	868	10	423	0	305	163	20
30, σ=0.3	70	838	22	409	4	312	161	21
30, σ=0.5	158	813	87	384	37	345	224	29
30, σ=0.1, a_1=0.8	23	892	3	452	0	311	138	16
30, σ=0.2, a_1=0.8	49	850	7	439	0	301	139	18
30, σ=0.3, a_1=0.8	93	818	17	421	5	301	159	20
30, σ=0.5, a_1=0.8	217	806	66	397	29	326	200	23
30, aver. inflow	548	826	18	465	1	280	213	21
60, σ=0.0	0	741	1	137	0	203	147	20
60, σ=0.1	1	697	3	137	0	190	153	21
60, σ=0.2	21	661	12	145	1	205	180	24
60, σ=0.3	74	687	25	158	3	246	214	27
60, σ=0.5	183	732	135	187	47	311	304	36
60, σ=0.1, a_1=0.8	0	691	1	146	0	202	147	20
60, σ=0.2, a_1=0.8	47	687	4	165	0	219	161	23
60, σ=0.3, a_1=0.8	157	707	21	179	4	248	200	27
60, σ=0.5, a_1=0.8	439	752	109	212	34	313	258	34
60, aver. inflow	495	729	24	253	0	190	273	36
90, σ=0.0	0	627	0	78	0	202	152	26
90, σ=0.1	0	591	2	84	0	198	139	25
90, σ=0.2	16	596	12	100	0	212	170	28
90, σ=0.3	48	637	27	120	3	243	212	32
90, σ=0.1, a_1=0.8	3	613	1	95	0	211	129	25
90, σ=0.2, a_1=0.8	42	662	5	129	0	221	151	27
90, σ=0.3, a_1=0.8	154	698	12	149	0	252	180	30
90, aver. inflow	595	730	34	193	0	204	321	49
120, σ=0.0	0	636	0	73	0	209	125	25

The total number of violations of the water level limits in different runs with a_1=0.8 are also shown in Table 43. Generally, compared with the case of a_1=0.0, the number of violations of the water level limits increases. For small errors and short forecast periods (30 days), the effect can be opposite, however. At worst, the additional autocorrelation more than doubles n_{WABS} compared with the case of using a_1=0.0. This is the case e.g. for Lake Päijänne for forecast periods of 60 or 90 days and large values of σ (σ=0.3 and σ=0.5).

The effect of the inaccurate forecasts on hydroelectric power production was also studied. Table 44 shows the results. The effects are calculated by comparing the results of different simulations with the results of the run using perfect forecasts of a time period of 120 days. In other words, it was set as the “global” optimum.

If the forecast period is shorter than 120 days, some losses in energy production exist even if the perfect forecasts are available. These losses are less than 1% of the maximum production but financially up to a few hundred thousands Euros per year for the forecast period of 30 days. The losses will increase if forecasts are inaccurate. If short forecasts are combined with the inaccuracies, losses can rise up to almost a million Euros annually. If the forecast length is kept constant and the forecast error is increased by 0.1 (e.g. from σ=0.1 to σ=0.2), the average decrease in hydropower production is of the order of magnitude from 0.1 to 0.6% during the period 1965-2004. This means about 1.7-8.0 GWh (40 000 € - 235 000 €) annually. If the operation of the system is based on the inflow forecasts of a time period of three months (a_1=0.0), the increased accuracy of the model from σ=0.3 to σ=0.2 would benefit the power companies as much as 8.0 GWh (235 000 €) per year. At the same time, the flood and drought problems would decrease significantly. The number of the fixed absolute water level violations (n_{WABS}) would more than halve in Lake Päijänne and Lake Ruotsalainen.

Generally with the smaller errors (σ=0.1 or σ=0.2), the longer forecasts will give additional gain for the hydroelectric power companies supposing that the errors do not increase as the forecast lead time gets longer. If the errors are larger, the use of longer forecasts may even cause more losses than benefits. The results concerning hydroelectric power production by using a_1=0.8 are also shown in Table 44. The energy production is higher compared with the case of a_1=0.0.

The results of the simulations where the average historical inflow sequence is used as a forecast give a possibility to compare the cases of “perfect forecasts” versus “no forecasts”. In reality, forecast accuracy is somewhere between these two extremes. If a system can be operated better with the average historical inflow than with the forecasts of the hydrological models or the regression equations, there is no reason to maintain the forecast system. The results corresponding to the average flows are poor, however. The value of the objective function is about as poor as in the case of using σ=0.5. In the light of hydropower production, the use of the historical average as the inflow forecast is not as crucial. Rather, the problems are related to the flood and drought problems (Table 43). Hydropower production would decrease by about 0.6 % (7.4 GWh/a) if the average inflow (90 days) is used as a forecast instead of the perfect inflow of a time period of 120 days.

Table 44. Hydroelectric power production in the River Kymijoki system by using forecasts of different accuracies and lengths compared with results of using perfect forecasts of a lead-time of 120 days. Simulation period 1965-2004.

Forecast length and accuracy	Change compared with results of using perfect forecasts of a lead-time of 120 days			
[d]	MWh %	€ [%]	[MWh/a]	[€/a]
120, σ=0.0	0.0	0.0	0	0
30, σ=0.0	-0.9	-0.8	-11600	-315000
30, σ=0.1	-1.0	-1.0	-12900	-354000
30, σ=0.2	-1.2	-1.2	-15600	-432000
30, σ=0.3	-1.4	-1.4	-18500	-520000
30, σ=0.5	-2.0	-2.0	-26100	-744000
30, σ=0.1, a_1=0.8	-1.0	-0.9	-12300	-336000
30, σ=0.2, a_1=0.8	-1.1	-1.0	-14000	-384000
30, σ=0.3, a_1=0.8	-1.3	-1.2	-16700	-464000
30, σ=0.5, a_1=0.8	-1.9	-1.8	-24300	-687000
30, aver. inflow	-0.9	-0.9	-12000	-328000
60, σ=0.0	-0.4	-0.3	-4800	-119000
60, σ=0.1	-0.6	-0.5	-7500	-198000
60, σ=0.2	-1.0	-1.0	-13500	-375000
60, σ=0.3	-1.5	-1.5	-19500	-548000
60, σ=0.5	-2.5	-2.5	-32300	-931000
60, σ=0.1, a_1=0.8	-0.5	-0.4	-6300	-162000
60, σ=0.2, a_1=0.8	-0.8	-0.7	-10300	-279000
60, σ=0.3, a_1=0.8	-1.3	-1.2	-16500	-459000
60, σ=0.5, a_1=0.8	-2.3	-2.3	-30300	-859000
60, aver. inflow	-0.6	-0.6	-8100	-210000
90, σ=0.0	-0.1	-0.1	-1500	-31000
90, σ=0.1	-0.4	-0.3	-4800	-127000
90, σ=0.2	-0.9	-0.8	-11000	-311000
90, σ=0.3	-1.5	-1.5	-19100	-547000
90, σ=0.1, a_1=0.8	-0.3	-0.2	-3600	-93000
90, σ=0.2, a_1=0.8	-0.7	-0.6	-8700	-239000
90, σ=0.3, a_1=0.8	-1.1	-1.1	-13700	-391000
90, aver. inflow	-0.6	-0.5	-7400	-196000

In the above presentation, the average values of the 15 independent runs were presented. As in the case study of Lake Pyhäjärvi, the random ε-sequence in the Equation 4-2 affects the results. Fifteen independent runs will contain neither the worse nor the best sequence in the light of the variables studied. In the case study of River Kymijoki, the effect of the ε-sequence on the results was stronger for the bigger values of σ: the variation between the results of the 15 independent runs increased considerably as a function of σ. Because of the large variances, differences in the mean values of the objective function between the results for the different values of σ were not always statistically significant (Figure 44). However, if hydropower production or the number of violations is studied, the dependence of the result on σ is much larger than that on the ε-sequence. Thus, it is reasonable to concentrate on analysing the average values of the independent runs for each σ.

4.4 Reliability of simulated annealing

Because of the heuristic nature of the simulated annealing algorithm, optimal solutions are not guaranteed. The reliability of the algorithm is dependent on the chosen parameter values and on the proper selection of the neighbourhood from which new candidate solutions are chosen.

In the case study of Lake Pyhäjärvi, the results were not very sensitive to the cooling schedule. This was mainly due to the optimisation problem that was not too difficult to solve. The parameter values that were used (Table 36) were chosen based on the test runs. In Table 45 an example is given. Forecasts of a time period of 90 days were used and thus, 18 variables were optimised. The period from 1967 to 2004 was considered with perfect knowledge of the inflow of the forthcoming period and this information was updated every 15 days. The whole simulation period was run through ten times for each of the parameter sets. The average values of the results are given in Table 45. The results are not very different in the light of n_{VIOL} and thus the selection of the values of the parameters was based mainly on the consumed computer time resulting in favouring the smaller values of α and L.

Table 45. The effect of the optimisation parameters on the results in the case study of Lake Pyhäjärvi.

α	L	G(R)	G(R) St.dev.	n_{WABSU}	n_{WABSL}	n_Q	n_{WOBJ}
95	100	-21160000	850000	0	0	830	265
95	50	-21390000	720000	0	0	824	265
90	100	-21690000	520000	0	0	834	265
90	50	-21080000	600000	0	0	813	264
85	100	-21440000	490000	0	0	834	265

To improve the reliability of the results, several parallel runs were made for each of the optimisation problems and the best result was finally chosen. The number of the parallel runs was also chosen based on the test runs. In the case study of Lake Pyhäjärvi, five parallel runs were used in the optimisation. The initial state was set as explained in Chapter 4.1.4.1. Three runs were based on the stochastic initial state and one for each other strategy. Because the problem was not too complicated, less than five parallel runs might well have been enough. Usually, the independent walkers ended up with equal or almost equal results and the release sequences seemed intuitively valid. Therefore, the optimisation algorithm can be considered reliable and the number of parallel runs was not increased.

In the case study of River Kymijoki, the optimisation problem was more difficult. The assessment of the performance of the algorithm was also difficult because of the nature of the cost functions. Quite similar release sequences could give deviant results because of the subjectively chosen, third degree penalty functions. Occasionally, the results of different runs appeared to be considerably different in the light of the value of the objective function and hence, it was justified to require more parallel runs. In addition, the standard deviation of the results of the parallel runs decreased as a function of consumed computer time. In the light of the release sequences and water levels, the differences between the parallel runs were not so large, however. Thus, only three parallel runs were used. In most cases, the best results were obtained by using the current solution extrapolated with a constant release for the last 15 days of the forecast period as an initial solution; see Chapter 4.1.4.1. Table 46 gives an example of the sensitivity of the optimisation to the schedule parameters α and L in the case study of River Kymijoki. The whole simulation period was run through five times with each of the parameter combinations using the perfect inflow forecast of a time period of 90 days and an update interval of 15 days. The values shown are averages of these runs.

Table 46. The effect of the optimisation parameters on the results in the case study of River Kymijoki.

Length of the forecast [d]	α	L	G(R) Average	G(R) St. dev
90	0.8	200	1252100000	1600000
90	0.8	400	1259100000	2200000
90	0.8	600	1261000000	1800000
90	0.8	1000	1261700000	1700000
90	0.9	200	1258300000	2300000
90	0.9	400	1261200000	900000
90	0.9	600	1261800000	700000
90	0.9	1000	1263600000	400000

The value of the objective function increases as a function of time consumed for the optimisation and the value seems to approach asymptotically the value assumed to be the global optimum. However, the approach velocity is slow and because the time available for the calculations was limited, a compromise had to be made between the parameters and the accuracy of the result.

Based on the results presented in Table 46, the value of α was set to α=0.90 in the optimisation of a time period of 90 days. Secondly, the value of L was set to L=400. Compared with the results given by the parameter values α=0.90 and L=1000, the time consumed in the calculations was about 40% less but the value of the objective function was only about 0.2% less. The effect on hydropower production is even less significant. Therefore, the use of the chosen parameter values is justified, but the inaccuracy of the optimisation should be taken into account when the results are analysed. The chosen parameter values for the forecasts of different lengths were presented in Table 37.

Because of the heuristic nature of the algorithm, one cannot assume that the optimised release sequence is optimal for the given inflow forecasts. The effect of the algorithm on the results can be approximated by using perfect forecasts and by optimising the same problem several times in a row and studying the results. In both case studies, the simulation period was run through 15 times with perfect forecasts and by updating the forecasts at every 15 days. In the Lake Pyhäjärvi case study, the standard deviations of the value of the objective function for the whole simulation period are about 1 to 4% of the average values. Also in the case study of the River Kymijoki system, the standard deviations are low compared with the mean values. The deviations varied from 2.5% in the case of the forecasts of a time period of 30 days to clearly under 1% in the case of longer forecasts. Differences are even smaller if hydroelectric power production is studied. There are some differences in n_{WABS}, n_{WOBJ} and n_Q between the results especially in the River Kymijoki system. The most sensitive are the variables describing The Lake Pyhäjärvi in Iitti, which is reasonable because of the small size of the lake. The order of magnitude, however, remains similar also for these variables. Thus, the effect of the chosen optimisation algorithm on the results is arguably small.

Also the selection of the neighbourhood of the current solution affects the speed of the convergence of the algorithm. When the new neighbour is explored, the release change in an individual 5 days' period was set to 5 m^3/s in the River Kymijoki system (see Chapter 4.1.4.3). It was studied whether the increase of this step and the lengthening of the constant release sequence from 5 days would speed up the convergence. It turned out that with larger values, simulated annealing did not converge properly. Totally different neighbourhood strategies were not applied.

4.5 Discussion

4.5.1 Release optimisation

Simulated annealing was used in the optimisation. The use of the algorithm is justified. As the computer capacity has increased, it is not necessary to worry that much about the consumed computer time of a stochastic optimisation in the real-time operation of the lake-river systems, as individual optimisation problems are solved in seconds. At the same time, it is neither necessary to use linear functions nor to discretise the problem and therefore, the special characteristics of the problems are easily taken into account. Although the algorithm is easy to implement, the general use of simulated annealing in the optimal operation of a multi-reservoir system is not straightforward. This is due to the subjectively chosen parameter values for the algorithm. The selection of the parameter values requires a good knowledge of the characteristics of the problem. A poor selection of the parameters and an ineffective definition of the neighbourhood of the current solution may lead to a solution that is not even close to the optimal one. In addition, the computer time used in large scale problems increases considerably and unnecessarily.

In the main part of the study, releases were optimised purely based on the mean forecasts without using the confidence limits of the forecasts. However, as shown in Chapter 4.2.4, solving the same problem by taking into account the uncertainties related to the forecasts, the nature of the answers to the research questions remained similar. In practice, the approach to the operation of Lake Päijänne is such that during the spring flood season, releases are planned based on higher than mean forecasts to avoid flood damages in the lake and downstream (Marttunen and Järvinen, 1999), although many operation policies are simulated. Therefore, one can fairly state that the use of a single forecast is not very different from the practice still in use.

In this study, the optimisation problems were not solved, for comparison, by using any other optimisation algorithms and the optimal solutions were not available. However, the sensitivity analysis showed that in the two case studies, the results were not significantly dependent on the parameter values chosen for the algorithm. The values were set based on careful studies (Chapter 4.4). In addition, results were intuitively rational and independent runs of the whole simulation period ended up relatively close to each other, although almost 1000 independent, consecutive optimisation tasks were solved. By increasing the available computer time significantly, the results of the optimisation improved slightly, but the increase of the value of the objective function for the whole simulation period was less than 1%. The effect on the main variables studied was even less. Although it is obvious that different choices would impact the individual numbers analysed in the study, it is clear that the main results are relatively reliable.

Earlier, only a few papers have been published on the use of simulated annealing in reservoir optimisation. Teegaravapu and Simonovic (2002) presented the context and applied the algorithm for two systems, each containing four reservoirs. Their study suggested that simulated annealing could be used to obtain at least near-optimal solutions for the multi-period reservoir operation problems. Mantawy et al. (2003) used a more sophisticated algorithm and solved a long-term hydropower scheduling problem in a system of four reservoirs connected in series with improved results. Tospornsampan et al. (2005) used simulated annealing with promising results in the optimisation of multiple reservoirs in a case study of the Mae Klong system in Thailand. The present study strengthens the view that simulated annealing is a flexible algorithm in the release optimisation of multi-purpose lake-river systems.

4.5.2 Value of inflow forecasts

A multi-purpose single-reservoir system was studied by using the characteristics of Lake Pyhäjärvi located in the River Eurajoki basin. In addition, the multi-reservoir system of the River Kymijoki basin was studied. In both of the case studies the simulation period was first run through by using perfect inflow forecasts. When using perfect forecasts, the value of the inflow forecasts increased as the forecast period got longer: in Lake Pyhäjärvi up to 360 days and in Lake Päijänne up to 120 days. However, in Lake Pyhäjärvi the increase was small, when the forecast length of 5-6 months was exceeded and in the River Kymijoki system, the improvement of the operation was quite small when the forecast lead time of 2-3 months were lengthened. The errors in the forecast shorten the “reasonable” forecast lengths. If errors are small (σ=0.1), a forecast lead-time of at least 12 months could be used in Lake Pyhäjärvi. On the other hand, if forecast are poor (σ=1.0) only a forecast period of five months should be utilised. Generally, it seems that it is not worthwhile to use inflow forecast of a lead-time longer than 3-4 months in Lake Pyhäjärvi, if forecast accuracy simultaneously weakens significantly (e.g. from σ=0.1-0.3 to σ=0.5) (Figure 38). Compared with the Lake Pyhäjärvi system, more accurate and shorter forecasts should be used in the River Kymijoki system. In the River Kymijoki system, it is not necessarily valuable to lengthen the forecast period if forecast errors are larger than or equal to σ=0.3. The additional value of the longer forecasts is lost if forecast accuracy weakens significantly (e.g. from σ=0.1 to σ=0.2) regardless of the forecast length (Figure 44). If forecast errors increase as the forecast period gets longer, the impact of using longer forecasts may be negative.

The most important reason for the differences in the optimal forecast lengths of the two case studies is the live capacities of the systems. Large systems can utilise long-term information even though forecast errors are relatively large. On the other hand, small systems are very sensitive to forecast errors. Thus, the optimal forecast period depends mainly on the live capacity of the system - and naturally on the accuracy of the forecasts.

In the River Kymijoki system it seemed that the lake most vulnerable to forecast errors was, surprisingly, Lake Päijänne, the largest lake of the system. One reason for the vulnerability of Lake Päijänne could be the use of its live capacity to avoid larger floods downstream. The chosen cost functions may lead to a control where, for the benefit of the whole system, it is better to store floods in Lake Päijänne. This control causes small violations of its water level limits instead of leading the same flood downstream and causing more severe violations of water level limits in the smaller lakes. The cost of a 1 cm violation is equally large in each of the lakes, although there are much more properties in the shores of Lake Päijänne compared with smaller lakes downstream. The regulation of Lake Päijänne is also inefficient because of the inability to regulate the whole outflow. However, the costs for violating the objective water levels by a few centimetres are small in the model as well as in real-life. Thereupon, these limits are violated regularly by a centimetre or two because it benefits the operation of the whole system.

The problems related to the control of Lake Pyhäjärvi in Iitti (Kymijoki system) are due to its small live capacity. Even small errors in the inflow forecasts can cause severe water level limit violations because of the long update frequency of the forecasts compared to the number of days needed to fill the whole live capacity with the average inflow. However, the problems can be avoided, or the negative consequences can be decreased, if the upstream lakes are regulated so that the largest floods are smoothed before they enter Lake Pyhäjärvi. The better the forecasts, the better this can be done.

According to Takeuchi and Sivaarthitkul (1995), a forecast lead-time of approximately two months should be used for reservoirs with live capacity of 0.22 times the average annual inflow, that of 3 months for reservoirs of 0.5 times the annual inflow and at least that of 6 months for reservoirs of 1.0 times the annual inflow. These figures are dependent on forecast accuracy. The results of this study are similar. Depending on forecast accuracy, a forecast lead-time of about 1-3 months should be utilised in the River Kymijoki system (0.25 times the average inflow) and a lead-time of about 3-12 months in the Lake Pyhäjärvi system (0.57 times the average inflow). In addition to forecast accuracy and size of the system, also the shape of the hydrograph and the possible restrictions related to the release sequences affect the optimal lead-time of the forecasts.

The results can also be analysed in the light of hydropower production, water levels and release sequences. The system of Lake Pyhäjärvi can be operated in a way that the fixed, absolute upper and lower water level limits would not be violated, if perfect forecasts of a length of 90 days or longer were available (Table 38). Compared with hydroelectric power production by using the observed releases, the possibility of using a perfect inflow forecast of 360 days increased the power production by about 9%. The downstream power plants were not taken into account in the simulation. Thus, more variables should be taken into account in the real-time operation of the system. However, because the availability of perfect inflow forecasts would decrease the spillage and smooth the release sequence, it is quite likely that results would be similar, even if the missing variables were taken into account.

The use of the perfect inflow forecast would have increased hydropower production by 0.7% compared with the production for the observed releases in the River Kymijoki system. The relatively small increase may be a consequence of relatively good inflow forecasts used in the past in the real-time operation of the system. On the other hand, the relatively small live capacities (25% of the annual inflow) and the water level and discharge limitations of the lakes and the unregulated natural cascade in Kalkkinen restrict the possibilities in real time operation. Therefore, the chosen release strategy does not affect hydropower production considerably. In addition, in the simulations, strict objective water levels were set for the lakes in the River Kymijoki system. For example, in Lake Päijänne the objective water level limits used in the model are used in real-time operation only for the last few years. Thus, in history the live capacity of the system has been utilised much more effectively compared to the simulation. Although the difference in hydroelectric power production is relatively small, the numbers of water level limit violations of the observed and simulated cases differ significantly.

The study by Yeh et al. (1982) discussed a system with a live capacity of approximately 0.8 times the annual inflow. The gain of the perfect forecasts of a time period of three months for hydropower production was 6.48 percent compared with the status quo. Hamlet et al. (2001) showed that by advancing the forecasts of the snowmelt season by six months with the help of the indices of El Niño/Southern Oscillation (ENSO) and Pacific decadal oscillation (PDO), they could gain a financial benefit of about 7.6 percentage compared with the status quo in Columbia River (reservoir size 0.3 times average inflow).

Compared with the optimal operation, the use of short and inaccurate forecasts may cause losses of up to 10% in the financial value of hydropower production in the Lake Pyhäjärvi system (Figure 39). At the same time, violations of the absolute water level limits can not be avoided (Appendix G). Compared with the optimal operation (forecast period 120 days, perfect forecast), the use of short and inaccurate forecasts in the River Kymijoki system may cause losses of up to 2.5% annually in hydropower production (Table 44). Financially this can rise up to almost a million Euros annually. At the same time problems related to the water levels and releases in the regulated lakes are multiplied.

It was shown that by improving the forecast accuracy of the inflows of Lake Päijänne e.g. from σ=0.2 to σ=0.1, hydropower production in the River Kymijoki system can increase as much as 0.6% annually. It is important to notice that the additional benefit of more accurate forecasts is larger, if the initial forecasts are poor (Figure 38, Figure 44). In the Lake Pyhäjärvi system, hydropower production would increase about 1-3%, if the accuracy of the forecasts could be increased from σ=0.3 to σ=0.1. In addition, for effective operation of the systems, long-term forecasts should be utilised in both systems. Optimisation models should be used and as the case study of the River Kymijoki system showed, the whole system should be operated as an entity instead of maximising the operation of the individual units within the larger system. Especially the live capacities of Lake Ruotsalainen and Lake Konnivesi could be utilised more efficiently.

Maurer and Lettenmaier (2004) have collected the results of these types of studies. They compared the live capacities of the systems and the additional relative gain from the forecasts for hydropower production ("perfect forecasts" vs "no forecasts"). The gain for hydropower varies between 1-13.6% for systems whose live capacities vary from 0.3 to 3.0 times the annual inflow. It is natural that for very large reservoirs the value of long-term forecasts is relatively small because the capacity of the system to smooth the forecast errors is large. On the other hand, for very small reservoirs the additional value of the long-term forecasts is also small because the possibilities of the system to smooth the inflows are restricted. Thus, the relative additional value of the long-term forecasts is the highest for the mid-size reservoir systems but is in any case highly system specific. In the Lake Pyhäjärvi system hydropower production decreased by 3% and in the River Kymijoki system by 0.6% if historical daily averages were used as forecasts ("no forecasts") instead of perfect inflow forecasts. At the same time, flood and drought problems increased significantly.

Also the effect of the update frequency on the results was studied by using the case study of Lake Pyhäjärvi. It was shown that the value of the forecasts is dependent on the update frequency of the forecasts (Figure 40). This is true especially if the update frequency is sparse and the forecast period is short. If a long lead-time is used, the effect diminishes. In the case study of Lake Pyhäjärvi, the effect of the update frequency had more influence on the water level and release violations than on hydropower production. The effect of lengthening the update frequency on hydropower production is insignificant if perfect forecast are used. By using the error σ=0.5, hydropower production decreases by 1-2% if the update frequency is lengthened from 15 to 30 days. The effect is larger if the number of violations of the restrictions is studied. The effect is probably even more significant for the systems with smaller live capacities (e.g. River Kymijoki).

This result can also be seen as an evidence of the importance of using up to date information and observations in inflow forecasting. In Finland, especially during winters, some of the hydrologic data, useful in forecasting, are measured and updated approximately twice a month. For example, ground water levels and snow water equivalents are measured by using this frequency unless some special need or unusual hydrological conditions occur. In this study, the update frequency of the forecasts was set to 15 days. This is a long time, if the value of the short-term flood forecasts was studied. In long-term forecasting, however, it is rare that any significant new information, valuable for long-term forecasting, would occur more often than once in 15 days.

The aforementioned results were based on solving a deterministic problem where inflow I was assumed to be known. Also the stochastic problem was solved in the case study of Lake Pyhäjärvi. Again, the additional value of lengthening the forecast period from 5-6 months was small. The values of the objective function were slightly better compared with the results related to the deterministic problem if forecast errors were small. Hydroelectric power production decreased at the same time as the flood and drought problems decreased. Compared with the chosen “optimal operation”, the use of short and inaccurate forecasts can decrease hydropower production up to 18%. The additional value of the longer forecasts is lost if forecasts of about 3-6 months are used (depending on the initial accuracy) and the forecast accuracy decreases at the same time. Some of the issues related to the sensitivity and reliability of the study method and thus the results are discussed in the following chapters.

4.5.2.1 Artificial forecasts

The artificial forecast error was calculated based on the observed inflow volume of the forecast period (Equation 4-2). The absolute forecast error was then uniformly divided for the whole period. The approach is straightforward but at least three problems are related to it. Firstly, instead of dividing the error uniformly for the whole period, it would also have been possible to presume that the errors of the daily discharges would increase as the distance from the forecast date increases. In addition, if there are both dry and wet periods within the forecast period, the chosen approach will cause events where relatively larger forecast errors are generated for the dry periods than for the wet ones. The effects of the chosen approach on the results can only be guessed. Intuitively, forecast errors are smaller just after the forecast date when compared with errors in the daily forecasts up to six months ahead. However, there is no way to divide the errors objectively by using this approach either and thus the decreasing accuracy of the forecasts with respect to the forecast length was not taken into account. If a monthly time step had been used, these kinds of assumptions would not have been needed. On the other hand, by using a daily time-step it was possible to get more information about the system. Probably, the chosen approach improves the operation of the system and thus the results concerning the inaccurate forecasts. This is especially true for the lakes with a small live capacity, as no large, sudden errors exist in the inflow forecasts. On the other hand, the short update frequency of the forecasts might soften the effect; at least unless the largest errors occur during the first 15 days.

Secondly, the chosen approach leads to a situation where the timing of the forthcoming flood and drought periods is known: forecasts were inaccurate only concerning the volume of the inflows. This might affect the results especially for the case study of River Kymijoki because of the small live capacity of the system. Especially Lake Pyhäjärvi in Iitti would suffer from the mistiming of the forthcoming floods, even if the inflow sum forecasts were perfect. This is due to the small capacity of the lake compared with its average inflow. In the case study of Lake Pyhäjärvi in Säkylä, the effect would probably not be as critical because of the large live capacity. Also the high update frequency of the forecasts decreases the effect of mistiming the floods on the results in the approach used in this study.

Thirdly, by using different values for σ, the artificially generated, absolute forecast errors (Mm^3) are lower for the periods of low flow compared with flood seasons. This means that no floods are forecast for the periods where the observed inflows are low. On the other hand, it is possible to forecast drought for a high flow period. If σ is relatively small in the Equation 4-2, this is not a serious problem. For large σ, this is a drawback, however. The same problem was already noticed when σ was used as a goodness-of-fit criterion in the evaluation of the new forecast model developed in Chapter 3.

Lateral inflows to the system downstream of Lake Päijänne were considered to be perfectly known. In reality, forecasts of the lateral inflows are inaccurate and it is possible that the errors cumulate and significantly affect the operation of the system. This is especially true when a reservoir with a small live capacity such as Lake Pyhäjärvi in Iitti in the Kymijoki system is considered. The results attained relating the accuracy of the forecasts and the operation of the River Kymijoki system are thus somewhat biased. If similar forecasts for the lateral inflows had been used, the results would probably show the need for even more accurate forecasts in the operation of the system. The effect cannot be huge, however, because 75% of the discharge in the outlets of the Kymijoki River system originates from Lake Päijänne. All the above discussion about the accuracy and the reliability of the results is relevant. Moreover, the effects are parallel. All the simplifications and assumptions have decreased the effect of the forecast errors on the results especially in the River Kymijoki basin. Thus, it is possible that in reality the negative effect of the inaccurate forecasts on the regulation is stronger than approximated in this study.

4.5.2.2 Objective functions

The optimal solution of any model is optimal only with respect to the model itself, not necessarily with respect to the real system (Loucks and Van Beek, 2005). Also in this study, subjectively chosen loss functions were used. The results are dependent on this selection and thus, precise conclusions should be avoided. For example, both reservoir systems could probably be operated more efficiently with respect to hydropower production if the whole live capacity could be utilised through the year without any objective water levels. In practice, water level limits decrease the live capacity of the system.

The basis for the selection of the loss functions was the current operation policy of the system. The objective water levels were set on the basis of the recent studies on River Kymijoki, but in the case study of Lake Pyhäjärvi they were mainly set subjectively. The absolute water level limits are set in the regulation licenses except for the lower water level limit in Lake Ruotsalainen and limits in Lake Päijänne. These limits were subjectively set. In the case study of River Kymijoki, the loss functions were similar for each of the lakes. By putting more weight on the water level violations in Lake Päijänne, the flood and drought problems downstream had probably been larger. Now, the capacity of Lake Päijänne was used to avoid larger water level violations downstream.

The objective water levels were set for the 1st and the 15th of each month. At the same time, an update frequency of 15 days was used for the forecasts. Thus, during the simulation period the forecast dates varied between, for example, the first, tenth or, say 28th, of any month. As a consequence, the objective water levels are not at exactly the same spot for every optimisation problem, and sometimes only a single objective water level falls into the period of 30 days. If the forecast period is long, the effect on the results is insignificant, but for the short forecast lengths, it might underline the importance of hydropower production by using the maximum capacity of the hydropower plants at the expense of the water levels of the studied lakes. However, the most relevant results are related to the longer forecasts and therefore, this drawback is not considered that significant.

In the River Kymijoki basin, the financial costs caused by the high water levels have been studied (Eskola, 1999). The financial losses caused by floods for agriculture, forestry and buildings have been approximated. The curves relating these variables to the water level limits in the River Kymijoki basin were available, but they were not used. It is obvious that the whole system is operated much more strictly than on the basis of purely economic values. The absolute water level limits are obeyed although the economic losses caused by the violations would not be large.

The price of electricity has recently risen and this increases the financial value of the inflow forecasts. In this study, constant prices were used and an assumption was made that all produced electricity can always be sold immediately at the given price. In reality, the price of electricity is dependent on the market situation and that should also be taken into account in the release optimisation. In addition, one of the biggest benefits of hydropower production is the easy usage of power plants to control the variations in electricity consumption. Hydropower plants are easily shut down and turned on again. In this study, the usage of hydropower plants for control is not taken into account. This is a drawback, but the effects of using hydropower for control could not be taken into account because the electricity markets were not modelled. This is also the reason why the additional value of the inflow forecasts in the light of non-firm and firm electricity markets was not studied. As shown by Hamlet et al. (2002), earlier inflow forecasts can increase the possibility of making non-firm electricity delivery deals with a large additional economical value for hydropower companies.

The efficiency factors of the power plants were set constant in the study. Constant values were also used for the heads of the different plants except for the Vuolenkoski power plant. Hence, the need for hydraulic models was avoided. If these were taken into account, it is probable that slightly higher water levels would have been aimed at especially in the case study of Lake Pyhäjärvi. It is reasonable to assume that neither of these simplifications has affected the general results. This is supported by the fact that by using the observed release sequences, the hydropower production of the simulation model was close to the production reported by the power companies.

The results are analysed only in the light of the water level and release limit violations and hydroelectric power production. Ecological aspects such as breeding of fishes and nesting of birds are not studied in detail. It is supposed that the objective water levels that are set to take into account these matters, guarantee a good state of the lakes for breeding of different species. It is possible, however, that large forecast errors occurring in springtime may cause severe problems for nesting of birds although only occasional violations of the water level limits would occur. The value of the inflow forecasts for different seasons was not studied separately. For example, it might be reasonable to use longer forecasts for the seasons with a low inflow because the live capacity of the lake is larger compared with the average inflow of the period in question.

Despite the limitations and simplifications of the methodology discussed in the previous chapters, the results are in line with the outcomes of similar international studies. High accuracy of forecasts should be aimed at if reservoirs are small compared with annual inflow (Lake Päijänne). With large reservoirs, long-term forecasts should be utilised without focusing too much on accuracy (Lake Pyhäjärvi). Similar conclusions have been presented in the studies of Kim and Palmer (1997) and Takeuchi and Sivaarthitkul (1995).

4.5.3 Utilization of the results

The results of the two parts of this study can be combined. The usability of the new model in real time forecasting can be evaluated based on the results of the second part of this study. It was shown that if the distribution of the relative forecast errors is too wide, forecasts should not be used. Although in the first part of the study the forecasts were made for periods as long as six months, it was discovered in the second part that in the optimal operation of the River Kymijoki system only forecasts of lead-times up to 2-3 months are necessary. It is, however, of hydrologic interest to analyse the possibilities to forecast as far as six months ahead in these study basins. The accuracy of the new model for forecasting a period of three months ahead was about σ=0.16 (16%) on April 1 and σ=0.2 (20%) on October 1 and for forecasting a period of two months ahead about the same. These figures can be compared with the results in Figure 44, Table 43 and Table 44. The optimal forecast length for operation of the system by using forecasts of this accuracy is about 2-3 months. If compared with the optimal operation (4 months of perfect forecasts available), the use of the forecast model with this accuracy would cause losses less than 1% in hydropower production annually. Neither would the number of absolute water level violations increase dramatically, compared with the optimal operation. An improvement in the accuracy of the inflow forecasts from σ=0.2 to σ=0.1 in Lake Päijänne (a_1=0.0) would increase hydropower production by about 0.6% (6.0 GWh annually) in the River Kymijoki basin.

In Lake Pyhäjärvi the accuracy of the model was at best about σ=0.5 on April 1 and close to σ=1.0 on October 1, although these figures were slightly unreliable because of a few large errors. The optimal forecast length by using this kind of forecast would still be around 5-6 months. However, the losses in hydropower production caused by inaccurate forecast could be as much as 10%. By improving the forecast accuracy in Lake Pyhäjärvi from σ=0.5 to σ=0.3, hydropower production would increase about 2-3%.

Because the value of the inflow forecasts is dependent on the characteristics of the reservoirs, the usability of the forecasts models should not be evaluated purely based on the goodness-of-fit criteria. Also the system for which the forecast model is planned should be presented. For a very large reservoir, indicative forecasts are adequate and neither the maintenance of expensive forecast systems nor the expensive projects aiming at improvements in forecast accuracy is justified if the expected improvement in accuracy is small. For example, a model can be sufficiently good with a low value of R^2 if long-term forecasts are used and the target system has a large live capacity. An approach given in this study would be valuable in approximating the usefulness of the forecast model.

In Finland, the live capacities of the regulated lakes are relatively small. In some of the rivers that are most vulnerable to floods (e.g. River Kyrönjoki), the live capacity is only about 5% of the annual discharge. Normally, the live capacities of the watercourses are less than 100% of the annual runoff. The live capacities of the two most important Finnish rivers for hydroelectric power production, River Kemijoki and River Oulujoki, are around 40% and 60% of the annual discharge downstream, respectively. In 2005, a report was published on the possibilities to increase hydropower production in Finland (The Ministry of Trade and Industry, 2005). The potential energy lost as spill was approximated to be as much as 750 GWh annually. The potential increase in hydropower production by improving the accuracy of the inflow forecasts and thereupon regulation was not discussed. The issue was also ignored in the latest report on the possibilities to increase hydropower production in Finland (Oy Vesirakentaja, 2008)

Let us assume that the results of the study could be generalized. By using a conservative approximation that the results of the River Kymijoki system are valid all over Finland, it might be possible to increase hydroelectric power production by a minimum of 90 GWh (0.7%·13000 GWh) annually, if perfect inflow forecasts were available. Because the live capacities of the most important lake-river systems in Finland are larger than the live capacity of the River Kymijoki system, and because the whole outflow of Lake Päijänne can not be regulated, the additional value of a perfect forecast would probably be at least few percentages. In Lake Pyhäjärvi, where the live capacity is 57% of the annual inflow, it was approximated to be as much as 9%. Thus, the percentage might be as large as 5%. This would increase hydropower production by about 650 GWh annually. Thus it is possible that a great part of the spillage might be avoided without updating the regulation licenses if the accuracy of the long-term forecasts could be improved. At the same time flood and drought problems would decrease.

In reality, perfect forecasts are a utopia, and thus the potential increase in hydropower production by improving forecast accuracy lies below these approximations. As a matter of fact, improvement in accuracy is very difficult to achieve. As the case studies showed, the improvement in forecast accuracy in Lake Päijänne, for example, from σ=0.2 to σ=0.1 would benefit hydropower production in River Kymijoki system by about 0.6 % annually. In Lake Pyhäjärvi, the improvement in forecast accuracy, for example, from σ=0.5 to σ=0.3 would benefit hydropower production by about 2-3% annually. Thus if this is the accuracy of the current real-time forecast models, the possibilities of improving hydropower production in Finland by improving forecast accuracy might be as much as 0.5-2% (65 GWh-260 GWh). At the same time, flood and drought problems would, of course, decrease. These figures can be compared with approximations of the increase in production if the man-made reservoir in Vuotos in the River Kemijoki basin or the reservoir in Kollaja in the River Iijoki basin were built. The potential production increase based on the Vuotos reservoir is 325 GWh/a and on the Kollaja reservoir 200 GWh/a (Oy Vesirakentaja, 2008). Thus the possibilities for improving the forecast accuracy and operation policies should be further studied.

5 Conclusions

The main findings of the study can be summarised in the following points:

1. A non-parametric, long-term categorical discharge forecast model was developed. The analysis of forecast accuracy shows that the model is comparable with linear regression equations. This was true especially in forecasting the inflows to Lake Päijänne. For small basins and Lake Pyhäjärvi, the forecast accuracy of the model was modest on April 1 and poor on October 1.
2. The first effort was made for utilising indices of North Atlantic Oscillation for long-term inflow forecasting in Finland. Although the indices were finally utilised only in a single forecast model, significant correlation coefficients were found between NAO indices and the inflows of Lake Päijänne of a different length starting from April 1. Thus, further studies are needed.
3. In real-time operation of lake-river systems, the forecast length should be carefully selected. The use of too short forecasts causes losses compared with optimal operation even if perfect forecasts are available. On the other hand, the use of a lead-time of several months may cause losses compared with the use of shorter forecasts if the forecast accuracy is weak. Thus, the optimal forecast length is dependent on forecast accuracy.
4. The dependence between the accuracy of the forecasts and the benefits of the forecasts were studied for the first time in Finland. The results are in line with the outcomes of similar international studies. For large reservoirs, long-term forecasts should be utilised without giving too much a focus on the accuracy. On the other hand, for reservoirs that are small compared with the annual inflow, short forecasts with high accuracy should be aimed at. In Lake Pyhäjärvi this meant that inflow forecasts exceeding a lead-time of 5-6 months give very little additional value for the operation. In Lake Päijänne, this threshold was approximately 2-3 months.
5. In real-time forecasting, long-term forecasts should be updated regularly enough. The case study of Lake Pyhäjärvi showed that the losses in hydropower production by using an update frequency of 30 days compared with that of 15 days can be 1-2% if inaccurate forecasts are used. The losses are even more significant when water levels and release violation are taken into account.
6. It was estimated that by using existing regulation licenses, the maximum increase in hydropower production in Finland by improving forecast accuracy and by using sufficiently long forecasts might be as much as 0.5-2%.
7. In the River Kymijoki system, it would be possible to increase the overall electricity production by optimising the whole system at the same time instead of trying to maximise the production of the individual plants separately. The operation of the whole as an entity system would cause larger spring drawdowns especially in Lake Konnivesi-Ruotsalainen compared with the present situation.
8. Simulated annealing is a flexible optimisation algorithm for the operation of a lake-river system. Nonlinear cost functions are easily adapted and it is not

necessary to discretise the model. The high computational burden of the algorithm is not a problem because of the increased computational efficiency of computers. The results of the parallel runs in both of the case studies were equal or almost equal and were intuitively logical. Thus despite the heuristic nature of the algorithm it can be considered reliable.

6 Summary

This thesis aimed to improve knowledge of long-term inflow and streamflow forecasts in Finland. The study consists of two main parts. In the first part, a new type of index variable method for long-term inflow forecasting was developed and evaluated. In the second part, the value of long-term inflow forecasts was studied in general. The first specific objective of the study was to develop a long-term discharge forecast model that uses pattern recognition as an aid and does not use weather forecasts as input. The *k*-nearest neighbour rule and the minimum distance classifier were used to classify a forthcoming period into a wetness class based on the feature vector combined of the hydrologic observations from the basin. The accuracy of the model was studied in four case studies on two different dates. It was found that the accuracy of the method was comparable with the accuracy of the linear regression models, but with a simpler model structure.

The second and third specific objectives were addressed by studying two case studies, a single reservoir system, Lake Pyhäjärvi in the River Eurajoki basin and a multi-reservoir system, River Kymijoki. The aim was to determine the reasonable inflow forecast length in Finnish conditions and to identify the characteristics affecting this length. In addition, the aim was to assess the economic value of the long-term inflow forecasts and how this value depends on the forecast length, accuracy and update frequency. Moreover, the goal was to determine at which point the increasing errors of the forecasts overtake the additional value of the longer forecasts. In Chapter 4 it was shown that Lake Pyhäjärvi in the River Eurajoki basin should be operated by using forecasts of a lead-time from 3 to 12 months depending on the forecast accuracy (Figure 38). In Lake Päijänne, this length was shorter, no more than 1-3 months (Figure 44). The live capacity of Lake Pyhäjärvi is about 57% of the annual inflow while it is only about 25% in the River Kymijoki system. This is the most important reason for the differences in the optimal forecast lengths of the systems. In Lake Pyhäjärvi, the additional value of the longer forecasts is lost if the forecasts of a lead-time of 90 days or more are used and the forecast accuracy decreases significantly as the forecast period is lengthened. In Lake Päijänne, the additional value of longer forecasts is lost if the forecast accuracy decreases. This phenomenon is not dependent on the forecast length. In real-time operation, forecasts and planned operation should be updated regularly enough. It was shown that by lengthening the update frequency from 15 days to 30 days in Lake Pyhäjärvi, hydropower production would decrease by 1-2% and the number of violations would increase by about 20%, if the accuracy of the forecasts is around σ=0.5.

The increase in hydroelectric power production is 3.1% if perfect forecasts of a lead-time of 360 days are used in the Lake Pyhäjärvi system compared to the use of the average inflows as forecasts and a lead-time of 90 days. Similarly it is 0.6% in the River Kymijoki system (120 days perfect vs. 90 historical averages). At the same time, the flood and drought problems decrease more significantly.

The fourth specific objective of the study was to approximate the realistic possibilities of increasing hydroelectric power production in Finland only by improving the accuracy of the long-term inflow forecasts. By studying the live capacities of the most important lake-river systems for hydropower production and comparing these with the addressed case studies, Lake Pyhäjärvi and River Kymijoki, it was concluded that the realistic possibilities of increasing hydroelectric power production in Finland by improving forecast accuracy might be as much as 0.5-2% (65 GWh-260 GWh annually).

The fifth specific objective was to assess the possibilities of simulated annealing in optimisation of the lake-river systems. By using the algorithm in the aforementioned studies it was found out that the algorithm is very flexible and because of the increased computer capacity it is a respectable option for the optimisation algorithm in complicated optimisation problems.

Finally, the usability of the new forecast model, developed in the first part of the study, in real-time forecasting was evaluated by combining the two parts of the study. The method used for evaluating the long-term inflow forecasts is well suited for analysing the usefulness of the forecast model. It was concluded that the forecasts for Lake Päijänne were sufficiently accurate for real-time use. In Lake Pyhäjärvi, however, the accuracy of the model was poor outside the snowmelt season. However, because of the large live capacity of the lake, the consequences of poor forecasts are not as crucial as they would be in the River Kymijoki system.

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APPENDIX A. A map of the sub-basins north from Lake Päijänne

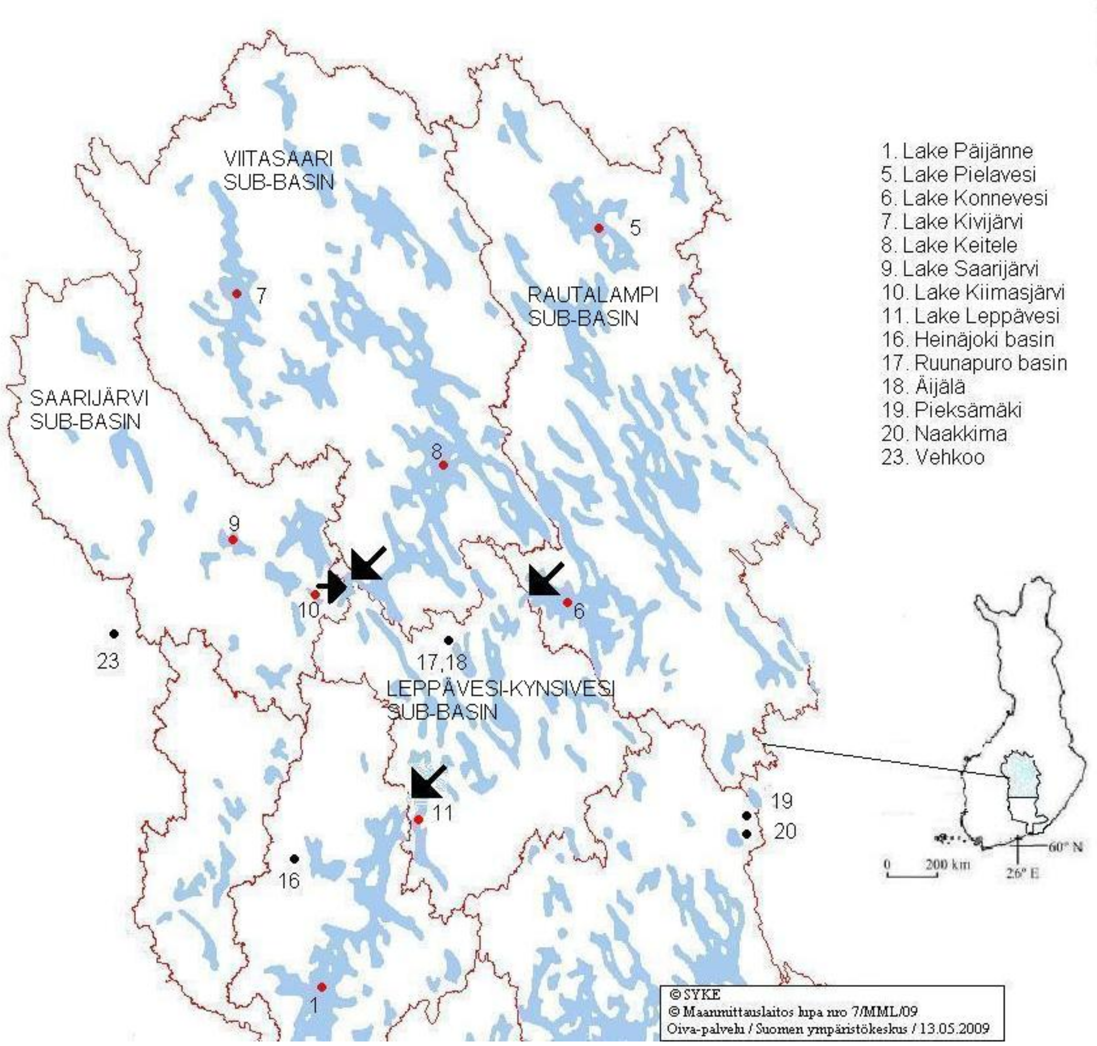

Figure A-1.1. A map of the River Kymijoki basin north from Lake Päijänne. Sub-basin outlets are pointed out by arrows.

APPENDIX B. Correlation matrix for Lake Päijänne on April 1

B-1 Correlation matrix on April 1 between the hydrologic variables in the basin and forthcoming accumulated inflow to Lake Päijänne.

	Q_{Apr}	$Q_{Apr\text{-}May}$	$Q_{Apr\text{-}Jun}$	$Q_{Apr\text{-}Jul}$	$Q_{Apr\text{-}Aug}$	$Q_{Apr\text{-}Sep}$	$\Sigma P_{Aug\text{-}Sep}$	$W_{Kivijärvi}$	$W_{Keitele}$	$W_{Saarijärvi}$	$W_{Kiimasjärvi}$
Q_{Apr}	**1.00**										
$Q_{Apr\text{-}May}$	**0.85**	**1.00**									
$Q_{Apr\text{-}Jun}$	**0.70**	**0.96**	**1.00**								
$Q_{Apr\text{-}Jul}$	**0.61**	**0.89**	**0.98**	**1.00**							
$Q_{Apr\text{-}Aug}$	**0.55**	**0.84**	**0.94**	**0.99**	**1.00**						
$Q_{Apr\text{-}Sep}$	**0.50**	**0.79**	**0.90**	**0.96**	**0.99**	**1.00**					
$\Sigma P_{Aug\text{-}Sep}$	0.22	0.30	0.35	0.35	**0.37**	**0.38**	**1.00**				
$W_{Kivijärvi}$	**0.33**	0.18	0.15	0.12	0.12	0.13	0.17	**1.00**			
$W_{Keitele}$	**0.66**	**0.50**	**0.45**	**0.38**	**0.34**	**0.30**	**0.46**	**0.54**	**1.00**		
$W_{Saarijärvi}$	**0.50**	**0.41**	**0.38**	0.30	0.24	0.19	0.09	**0.44**	**0.44**	**1.00**	
$W_{Kiimasjärvi}$	-0.09	0.03	0.09	0.13	0.25	0.34	0.55	0.02	0.09	0.12	**1.00**
$W_{Pielavesi}$	**0.70**	**0.71**	**0.70**	**0.66**	**0.62**	**0.59**	**0.42**	**0.44**	**0.80**	**0.45**	0.14
$W_{Konnevesi}$	**0.60**	**0.58**	**0.57**	**0.52**	**0.48**	**0.45**	**0.53**	**0.49**	**0.83**	0.36	0.18
$W_{Leppavesi}$	**0.59**	**0.45**	**0.37**	0.30	0.23	0.18	0.25	**0.62**	**060**	**0.61**	0.07
$W_{Vesijärvi}$	**0.60**	**0.44**	**0.36**	0.27	0.20	0.15	0.24	**0.59**	**0.76**	**0.56**	-0.27
ASWE1	0.25	**0.46**	**0.52**	**0.57**	**0.60**	**0.61**	0.18	-0.18	-0.02	-0.28	-0.04
ASWE2	0.11	**0.33**	0.39	**0.45**	**0.49**	**0.51**	0.13	-0.28	-0.19	-0.30	-0.06
$GW_{Pieksämäki}$	**-0.69**	**-0.52**	**-0.41**	**-0.32**	-0.24	-0.20	-0.24	**-0.56**	**-0.71**	**-0.52**	0.03
$GW_{Padasjoki}$	**-0.60**	**-0.42**	**-0.37**	-0.33	-0.29	-0.24	-0.20	**-0.45**	**-0.72**	**-0.84**	-0.01
$GW_{Äijälä}$	**0.47**	**0.46**	**0.44**	**0.37**	0.31	0.26	**0.51**	**0.48**	**0.63**	0.32	0.10
GW_{Vehkoo}	**0.51**	**0.40**	0.35	0.26	0.21	0.20	0.34	0.34	**0.81**	**0.47**	0.26
$GW_{Mutkala}$	**0.75**	**0.63**	**0.55**	**0.45**	0.37	0.30	0.24	**0.48**	**0.78**	**0.59**	-0.22
$GW_{Naakkima}$	**0.61**	**0.56**	**0.53**	**0.48**	**0.43**	**0.41**	**0.57**	0.33	**0.87**	0.35	0.21
$NAO_{Dec\text{-}Feb}$	**0.38**	**0.28**	**0.26**	**0.27**	**0.28**	**0.27**	0.27	**0.40**	**0.40**	0.28	-0.45
$\Sigma Q2_{Päijänne}$	**0.75**	**0.63**	**0.56**	**0.51**	**0.47**	**0.44**	0.33	**0.56**	**0.89**	**0.60**	0.10

B-2. Correlation matrix on April 1 in Lake Päijänne (cont.)

	$W_{Pielavesi}$	$W_{Konnevesi}$	$W_{Leppavesi}$	$W_{Vesijärvi}$	ASWE1	ASWE2	$GW_{Pieksämäki}$	$GW_{Padasjoki}$	$GW_{Äijälä}$	GW_{Vehkoo}	$GW_{Mutkala}$	$GW_{Naakkima}$	$NAO_{Dec-Feb}$	$\Sigma Q2_{Päijänne}$
$W_{Pielavesi}$	**1.00**													
$W_{Konnevesi}$	**0.94**	**1.00**												
$W_{Leppavesi}$	**0.63**	**0.57**	**1.00**											
$W_{Vesijärvi}$	**0.70**	**0.67**	**0.64**	**1.00**										
ASWE1	0.10	0.05	-0.15	-0.14	**1.00**									
ASWE2	-0.04	-0.12	-0.28	-0.29	**0.86**	**1.00**								
$GW_{Pieksämäki}$	**-0.69**	**-0.68**	**-0.65**	**-0.88**	0.10	0.25	**1.00**							
$GW_{Padasjoki}$	**-0.71**	**-0.64**	**-0.70**	**-0.83**	0.17	0.31	**0.59**	**1.00**						
$GW_{Äijälä}$	**0.64**	**0.71**	**0.57**	0.30	0.02	-0.08	**-0.42**	**-0.45**	**1.00**					
GW_{Vehkoo}	**0.75**	**0.77**	**0.46**	**0.66**	-0.10	-0.30	**-0.75**	**-0.69**	**0.53**	**1.00**				
$GW_{Mutkala}$	**0.71**	**0.71**	**0.61**	**0.87**	-0.02	-0.16	**-0.90**	**-0.77**	0.31	**0.69**	**1.00**			
$GW_{Naakkima}$	**0.87**	**0.89**	**0.45**	**0.66**	0.12	0.01	**-0.72**	**-0.57**	**0.46**	**0.81**	**0.72**	**1.00**		
$NAO_{Dec-Feb}$	**0.25**	0.16	0.30	**0.48**	0.03	-0.02	**-0.37**	**-0.37**	0.18	0.24	**0.42**	**0.35**	**1.00**	
$\Sigma Q2_{Päijänne}$	**0.85**	**0.82**	**0.76**	**0.81**	-0.02	-0.20	**-0.78**	**-0.87**	**0.61**	**0.78**	**0.86**	**0.80**	**0.26**	**1.00**

APPENDIX C. Correlation matrix for Lake Päijänne on October 1.

C-1 Correlation matrix on October 1 between the hydrologic variables in the basin and forthcoming accumulated inflow to Lake Päijänne.

	Q_{Oct}	$Q_{Oct\text{-}Nov}$	$Q_{Oct\text{-}Dec}$	$Q_{Oct\text{-}Jan}$	$Q_{Oct\text{-}Feb}$	$Q_{Oct\text{-}Mar}$
Q_{Oct}	**1.00**					
$Q_{Oct\text{-}Nov}$	**0.98**	**1.00**				
$Q_{Oct\text{-}Dec}$	**0.95**	**0.99**	**1.00**			
$Q_{Oct\text{-}Jan}$	**0.93**	**0.97**	**1.00**	**1.00**		
$Q_{Oct\text{-}Feb}$	**0.92**	**0.96**	**0.99**	**1.00**	**1.00**	
$Q_{Oct\text{-}Mar}$	**0.90**	**0.95**	**0.98**	**0.99**	**1.00**	**1.00**
$\Sigma Q2_{Päijänne}$	**0.91**	**0.87**	**0.82**	**0.80**	**0.79**	**0.77**
$\Sigma Q2_{Päijänne}$	**0.91**	**0.86**	**0.82**	**0.80**	**0.79**	**0.77**
$\Sigma P_{May\text{-}Sep}$	**0.86**	**0.84**	**0.79**	**0.77**	**0.76**	**0.75**
$W_{Kivijarvi}$	**0.72**	**0.68**	**0.65**	**0.64**	**0.64**	**0.64**
$W_{Keitele}$	**0.84**	**0.80**	**0.75**	**0.73**	**0.71**	**0.69**
$W_{Saarijarvi}$	0.33	0.33	0.27	0.24	0.23	0.23
$W_{Kiimasjarvi}$	0.19	0.22	0.19	0.17	0.15	0.17
$W_{Pielavesi}$	**0.85**	**0.83**	**0.81**	**0.80**	**0.79**	**0.78**
$W_{Konnevesi}$	**0.89**	**0.85**	**0.81**	**0.80**	**0.79**	**0.77**
$W_{Leppavesi}$	**0.93**	**0.90**	**0.86**	**0.84**	**0.83**	**0.81**
$W_{Vesijarvi}$	**0.65**	**0.60**	**0.52**	**0.49**	**0.47**	**0.44**
$GW_{Äijälä}$	**0.50**	**0.47**	**0.41**	**0.37**	**0.34**	0.32
$GW_{Mutkala}$	**0.75**	**0.72**	**0.67**	**0.64**	**0.63**	**0.63**
GW_{Vehkoo}	**0.59**	**0.60**	**0.60**	**0.59**	**0.58**	**0.57**
$GW_{Naakkima}$	**0.79**	**0.76**	**0.72**	**0.70**	**0.70**	**0.70**
$GW_{Pieksämäki}$	**-0.49**	**-0.48**	**-0.44**	**-0.40**	**-0.38**	-0.34
$GW_{Padasjoki}$	**-0.60**	**-0.59**	**-0.56**	**-0.53**	**-0.50**	**-0.49**
$NAO_{Jul\text{-}Sep}$	0.16	0.16	0.15	0.16	0.16	0.16

C-2 Correlation matrix on October 1 in Lake Päijänne (cont.)

	$\Sigma Q2_{\text{Päijänne}}$	$\Sigma Q4_{\text{Päijänne}}$	$\Sigma P_{\text{May-Sep}}$	$W_{\text{Kivijarvi}}$	W_{Keitele}	$W_{\text{Saarijarvi}}$	$W_{\text{Kiimasjarvi}}$	$W_{\text{Pielavesi}}$	$W_{\text{Konnevesi}}$	$W_{\text{Leppavesi}}$	$W_{\text{Vesijarvi}}$	$GW_{\text{Äijälä}}$	GW_{Mutkala}	GW_{Vehkoo}	GW_{Naakkima}	$GW_{\text{Pieksämäki}}$	$GW_{\text{Padasjoki}}$	$NAO_{\text{Jul-Sep}}$
$\Sigma Q2_{\text{Päijänne}}$	**1.00**																	
$\Sigma Q4_{\text{Päijänne}}$	**0.98**	**1.00**																
$\Sigma P_{\text{May-Sep}}$	**0.86**	**0.85**	**1.00**															
$W_{\text{Kivijarvi}}$	**0.74**	**0.74**	**0.79**	**1.00**														
W_{Keitele}	**0.88**	**0.89**	**0.87**	**0.82**	1.00													
$W_{\text{Saarijarvi}}$	0.34	0.33	**0.49**	**0.39**	**0.37**	**1.00**												
$W_{\text{Kiimasjarvi}}$	0.23	0.23	0.43	0.33	0.29	0.01	**1.00**											
$W_{\text{Pielavesi}}$	**0.86**	**0.87**	**0.86**	0.71	0.87	0.45	0.20	1.00										
$W_{\text{Konnevesi}}$	**0.91**	**0.92**	**0.86**	**0.70**	**0.87**	**0.47**	0.12	**0.90**	**1.00**									
$W_{\text{Leppavesi}}$	**0.95**	**0.95**	**0.84**	**0.72**	**0.90**	0.23	0.35	**0.87**	**0.90**	**1.00**								
$W_{\text{Vesijarvi}}$	**0.66**	**0.66**	**0.57**	**0.58**	**0.58**	**0.38**	0.16	**0.57**	**0.66**	**0.57**	**1.00**							
$GW_{\text{Äijälä}}$	**0.62**	**0.61**	**0.51**	**0.39**	**0.62**	0.34	0.33	**0.55**	**0.54**	**0.50**	0.28	**1.00**						
GW_{Mutkala}	**0.74**	**0.73**	**0.76**	**0.64**	**0.66**	**0.50**	0.08	**0.67**	**0.72**	**0.62**	**0.70**	**0.53**	**1.00**					
GW_{Vehkoo}	**0.68**	**0.72**	**0.61**	**0.58**	**0.61**	0.18	0.45	**0.49**	**0.57**	**0.62**	**0.64**	**0.48**	**0.59**	**1.00**				
GW_{Naakkima}	**0.75**	**0.73**	**0.72**	**0.71**	**0.73**	0.31	0.36	**0.62**	**0.76**	**0.72**	**0.54**	0.29	**0.50**	**0.39**	**1.00**			
$GW_{\text{Pieksämäki}}$	**-0.48**	**-0.49**	**-0.62**	**-0.37**	-0.30	-0.29	-0.47	-0.32	**-0.37**	**-0.52**	**-0.60**	0.23	**-0.67**	-0.35	**-0.59**	**1.00**		
$GW_{\text{Padasjoki}}$	**-0.64**	**-0.65**	**-0.51**	**-0.54**	**-0.50**	-0.02	-0.30	**-0.40**	**-0.55**	**-0.47**	**-0.71**	-0.05	**-0.71**	**-0.61**	**-0.49**	**0.59**	**1.00**	
$NAO_{\text{Jul-Sep}}$	0.17	0.14	0.10	0.07	0.09	0.06	-0.09	0.03	0.12	0.12	0.16	0.22	0.22	0.36	0.13	0.13	-0.04	**1.00**

APPENDIX D. Correlation matrix for Ruunapuro on April 1.

D-1. Correlation matrix for Ruunapuro on April 1.

	Q_{Apr}	$Q_{Apr\text{-}May}$	$Q_{Apr\text{-}Jun}$	$Q_{Apr\text{-}Jul}$	$Q_{Apr\text{-}Aug}$	$Q_{Apr\text{-}Sep}$	ASWE	Fr_{field}	Fr_{forest}	$\Sigma Q2_{Ruunapuro}$	$GW_{Äijälä}$	$\Sigma P_{Aug\text{-}Oct}$	$SM_{Äijälä}$
Q_{Apr}	**1.00**												
$Q_{Apr\text{-}May}$	**0.49**	**1.00**											
$Q_{Apr\text{-}Jun}$	**0.40**	**0.94**	**1.00**										
$Q_{Apr\text{-}Jul}$	**0.31**	**0.85**	**0.95**	**1.00**									
$Q_{Apr\text{-}Aug}$	0.21	**0.70**	**0.83**	**0.94**	**1.00**								
$Q_{Apr\text{-}Sep}$	0.15	**0.61**	**0.75**	**0.87**	**0.97**	**1.00**							
ASWE	0.15	**0.59**	**0.62**	**0.68**	**0.66**	**0.62**	**1.00**						
Fr_{field}	**0.41**	**0.43**	**0.37**	0.31	**0.35**	0.32	0.12	**1.00**					
Fr_{forest}	**0.40**	**0.45**	0.30	0.20	0.17	0.13	-0.01	**0.74**	**1.00**				
$\Sigma Q2_{Ruunapuro}$	0.18	0.03	-0.04	-0.03	0.07	0.06	**-0.32**	**0.39**	0.27	**1.00**			
$GW_{Äijälä}$	0.12	0.21	0.17	0.07	0.08	0.08	-0.33	**0.46**	0.42	0.29	**1.00**		
$\Sigma P_{Aug\text{-}Oct}$	0.02	0.20	0.19	0.20	0.25	0.27	0.10	0.20	0.01	0.14	**0.57**	**1.00**	
$SM_{Äijälä}$	**0.63**	-0.26	-0.40	-0.39	-0.37	-0.45	-0.38	0.13	0.20	0.46	-0.04	**-0.58**	**1.00**

APPENDIX E. Correlation matrix for Heinäjoki on April 1

E-1. Correlation matrix for Heinäjoki on April 1

	Q_{Apr}	$Q_{Apr-May}$	$Q_{Apr-Jun}$	$Q_{Apr-Jul}$	$Q_{Apr-Aug}$	$Q_{Apr-Sep}$	ASWE	Fr_{field}	Fr_{forest}	$\Sigma Q2_{Heinäjoki}$	$\Sigma Q4_{Heinäjoki}$	GW_{Vehkoo}	$\Sigma P_{Aug-Oct}$
Q_{Apr}	**1.00**												
$Q_{Apr-May}$	**0.38**	**1.00**											
$Q_{Apr-Jun}$	0.27	**0.93**	**1.00**										
$Q_{Apr-Jul}$	0.19	**0.86**	**0.95**	**1.00**									
$Q_{Apr-Aug}$	0.09	**0.67**	**0.84**	**0.93**	**1.00**								
$Q_{Apr-Sep}$	0.06	**0.59**	**0.77**	**0.86**	**0.98**	**1.00**							
ASWE	0.24	**0.72**	**0.71**	**0.71**	**0.63**	**0.61**	**1.00**						
Fr_{field}	-0.06	0.11	0.09	0.04	0.05	0.01	0.07	**1.00**					
Fr_{forest}	0.04	0.19	0.08	0.02	-0.03	-0.09	0.14	**0.86**	**1.00**				
$\Sigma Q2_{Heinäjoki}$	0.29	0.04	-0.03	-0.08	-0.04	-0.05	-0.26	0.27	0.30	**1.00**			
$\Sigma Q2_{Heinäjoki}$	0.28	0.04	-0.02	-0.06	-0.01	-0.02	-0.25	0.26	0.29	**0.96**	**1.00**		
GW_{Vehkoo}	0.12	-0.04	-0.04	-0.17	-0.07	-0.04	-0.28	**0.57**	0.31	**0.52**	**0.57**	**1.00**	
$\Sigma P_{Aug-Oct}$	0.10	0.11	0.16	0.09	0.10	0.08	-0.14	0.08	0.04	-0.02	-0.05	0.33	**1.00**

APPENDIX F. Examples of the inflow forecasts for Lake Päijänne on April 1.

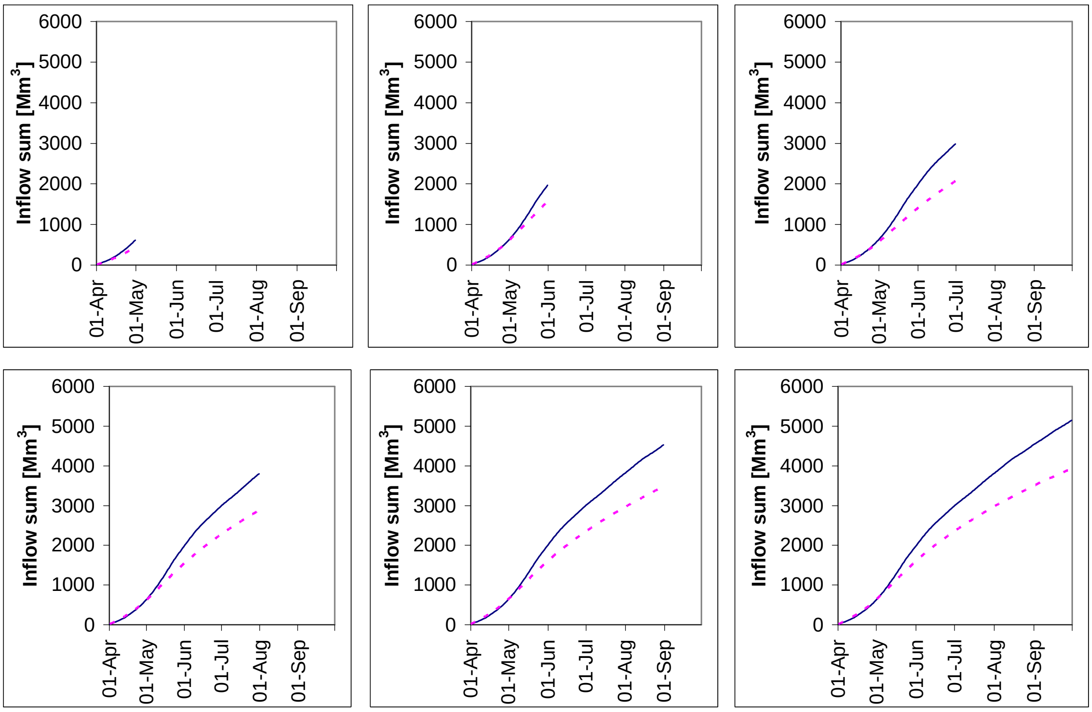

Figure F-1.1. Forecasts for different lead times on April 1 for 1977 using the models shown in Table 7. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

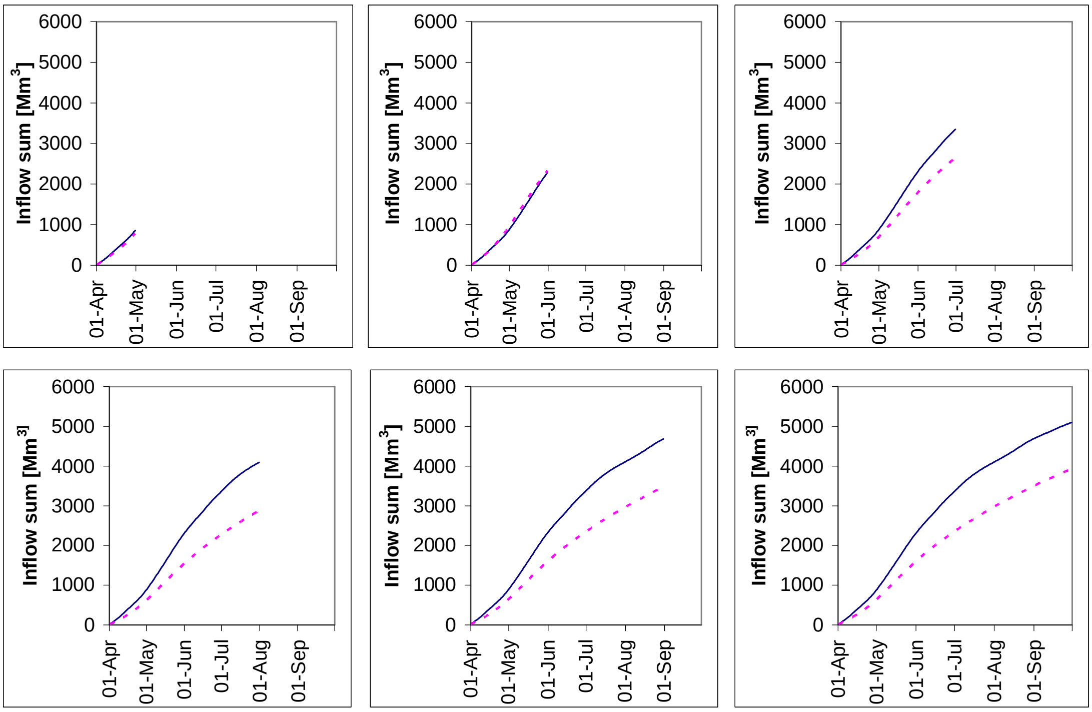

Figure F-1.2. Forecasts for different lead times on April 1 for 1982 using the models shown in Table 7. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

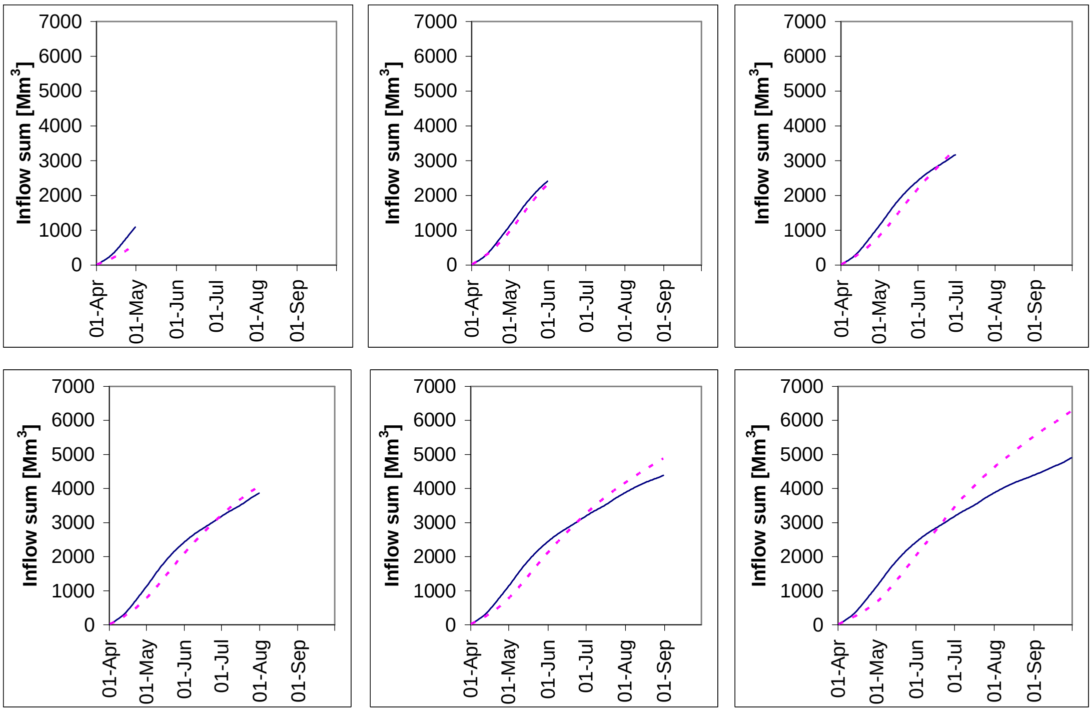

Figure F-2.1. Forecasts for different lead times on April 1 for 1984 using the models shown in Table 7. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

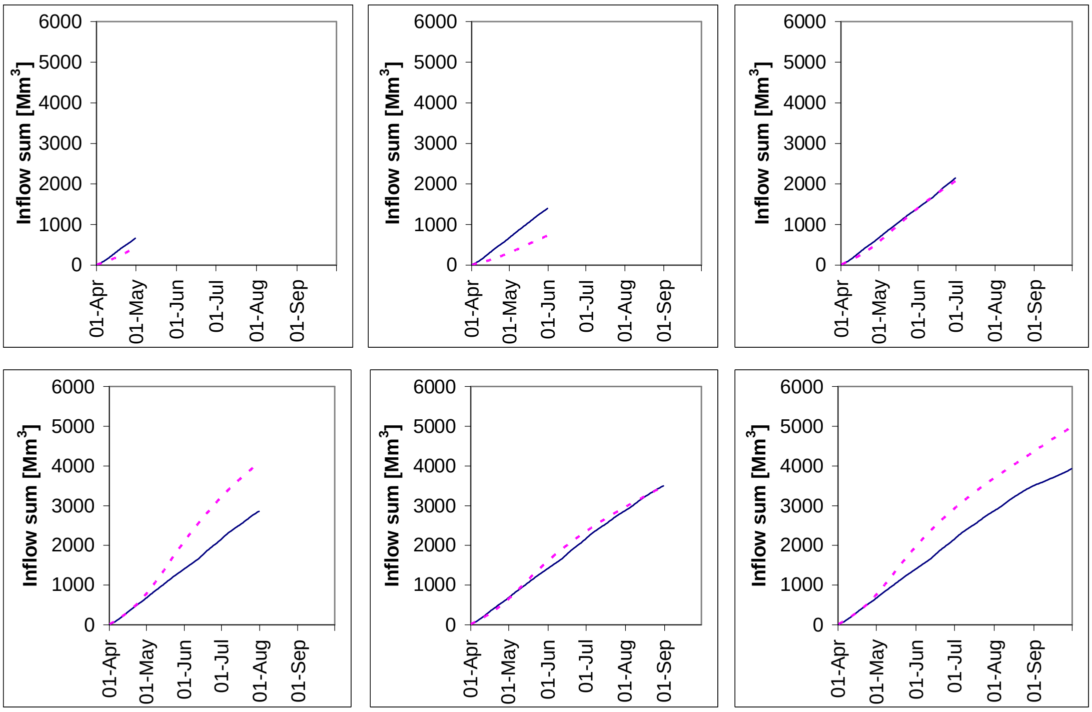

Figure F-2.2. Forecasts for different lead times on April 1 for 1991 using the models shown in Table 7. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

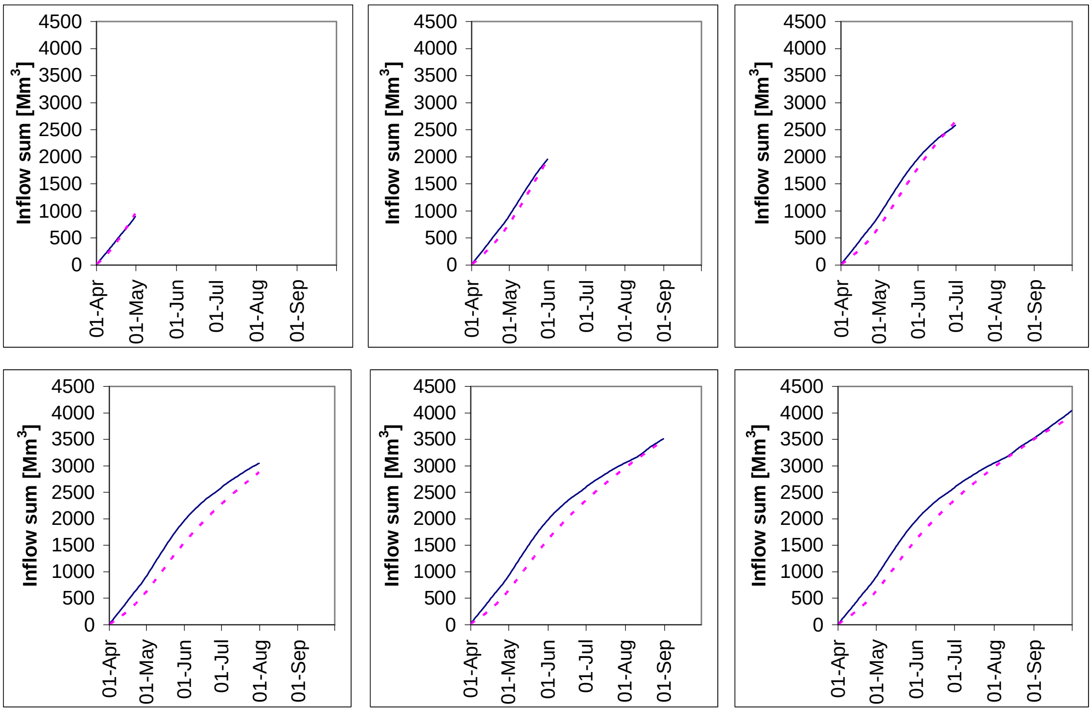

Figure F-3.1. Forecasts for different lead times on April 1 for 1992 using the models shown in Table 7. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

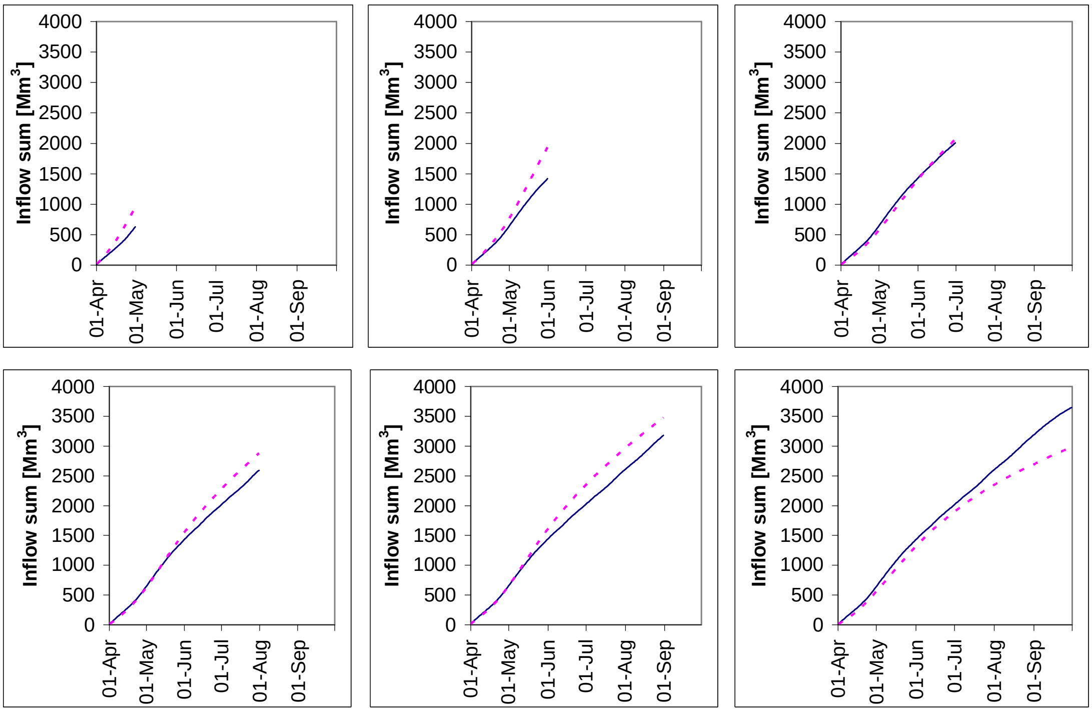

Figure F-3.2. Forecasts for different lead times on April 1 for 1993 using the models shown in Table 7. Darker line indicates the observation and lighter (dashed line) indicates the forecast.

APPENDIX G. Dependence between forecast accuracy and length and number of violations in regulation of Lake Pyhäjärvi.

Forecast length [d]	Accuracy of the forecast σ	n_{WABSL}	n_{WABSU}	n_Q	n_{WOBJ}	n_{VIOL}	Percentage increase of n_{VIOL} compared with the case of 360 days' perfect forecasts
360	0	0	0	146	212	358	0
90	average	98	335	907	451	1791	401
120	average	35	334	771	434	1574	340
30	0	408	30	990	524	1952	446
30	0.1	413	40	1005	517	1974	452
30	0.3	438	84	1037	501	2059	476
30	0.5	450	116	1061	492	2118	492
30	1	483	189	1265	498	2434	581
60	0	12	0	1013	345	1370	283
60	0.1	9	7	1032	338	1386	288
60	0.3	11	19	1076	335	1441	303
60	0.5	21	46	1225	348	1639	358
60	1	75	152	1723	405	2355	558
90	0	0	0	823	264	1088	204
90	0.1	0	4	861	261	1126	215
90	0.3	0	7	957	266	1231	244
90	0.5	0	22	1141	291	1455	307
90	1	39	140	1855	372	2406	573
120	0	0	0	667	239	906	153
120	0.1	0	4	708	237	949	165
120	0.3	0	11	844	237	1092	205
120	0.5	0	32	1080	264	1376	285
120	1	41	93	1924	348	2406	573
150	0	0	0	595	224	819	129
150	0.1	0	1	652	222	876	145
150	0.3	0	7	821	230	1059	196
150	0.5	5	22	1106	259	1392	289
150	1	31	94	2022	338	2484	594
180	0	0	0	538	217	755	111
180	0.1	0	3	559	213	775	117
180	0.3	5	6	765	228	1004	181
180	0.5	1	32	1092	257	1381	286
180	1	47	112	2130	338	2628	635
270	0	0	0	275	217	492	38
270	0.1	0	1	287	220	507	42
270	0.3	3	7	651	229	889	149
270	0.5	1	44	1187	262	1494	318
270	1	32	124	2480	355	2992	737
360	0	0	0	146	212	358	0
360	0.1	0	2	231	218	450	26
360	0.3	0	8	506	225	738	106

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