

Diploma Thesis

Impact of hydrological model calibration on the uncertainty of hydrological projections

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Abstract

Models are an important tool for the future water resource management. They allow us to gauge the impacts of climate change and depict changes in the water cycle. However, one of the most used types of hydrological models, the rainfall-runoff model, needs to be calibrated and validated via observational data before it can be used for predictions. This calibration is one of several sources of uncertainty for climate simulations with rainfall-runoff models. The higher the uncertainties, the less efficient are future water usage plans based on the models.

The research objectives of this thesis are 1.) to compare the four different calibration variants of a conceptual hydrological model for several different calibration periods in terms of efficiency, 2.) to examine the projections of mean annual and seasonal discharge based on six different climate scenarios representing four shared socio economic pathways, and 3.) to evaluate the uncertainty of hydrological projections of annual and seasonal discharges. All this is done for the Thaya catchment, consisting of the southern parts of Czechia and northern parts of Austria. For the variants a lumped model, a semi-distributed model, a distributed model and a semi-distributed model with additional snow data are used. The first three types of models are calibrated for periods 1986–1995, 1991–2000 and 1996–2005, the snow model for 1996–2005 and 2001–2010. The validation period is 2011–2019 for the Czech subcatchments and 2011–2017 for the Austrian subcatchments. The applied climate models are CMCC-ESM2, EC-EARTH3, GFDL-ESM4, MPI-ESM1.2-HR, MRI-ESM2.0 and TaiESM1 with the shared economic pathways SSP 126, SSP 245, SSP 370 and SSP 585 and projections for the year 2030.

While the distributed model performs the best for the calibration and validation, all calibration variants generally perform well. There are no spatial patterns in terms of altitude for the used efficiency values or for the calibrated parameters.

As for the hydrological projections the SSPs 245, 370 and 585 often show similar patterns for seasonal change in discharge, while SSP 126 differs vastly. For the climate models, CMCC generally leads to either small decreases or increases, while all other models tend to bring about significant decreases in seasonal discharges. The highest declines in discharge usually are from April to June.

As for the uncertainties, the differences in climate models lead to smaller uncertainties than the different calibration variants. Here it could also be seen that the calibration variant with the best effectiveness does not necessary lead to the smallest uncertainties. As for seasonal changes in discharge, the smallest uncertainties often times are in June. No such consistent pattern can be seen for the biggest uncertainty. There are no definitive findings about which SSP pathway leads to the biggest uncertainty.

For the annual changes in discharge the different calibration variants show no significant differences for the various SSPs and climate models.

Kurzfassung

Modelle sind ein wichtiges Werkzeug für das zukünftige Wasser Ressourcen Management. Durch sie ist es uns möglich, die Auswirkungen des Klimawandels abzuschätzen und Änderungen im Wasserkreislauf abzubilden. Eines der am meisten genutzten Arten von hydrologischen Modellen, das Niederschlags-Abfluss Modell, muss jedoch mit Hilfe von Beobachtungsdaten geeicht und validiert werden, bevor es für Vorhersagen genutzt werden kann. Diese Eichung ist eine von mehreren Quellen von Unsicherheiten von Klimasimulationen mit Niederschlags-Abfluss Modellen. Je höher diese Unsicherheiten werden, desto weniger effizient sind die Wassernutzungspläne für die Zukunft, welche auf den Modellen basieren.

Die Forschungsziele dieser Diplomarbeit sind 1.) die vier verschiedenen Eichungsvarianten des konzeptionellen hydrologischen Modelles für verschiedene Eichungsperioden in Bezug auf Effektivität zu vergleichen, 2.) die Projektionen der durchschnittlichen jährlichen und saisonalen Abflussänderungen basierend auf sechs verschiedenen Klimaszenarien und vier sozioökonomischen Pfaden zu untersuchen, und 3.) die Unsicherheiten der hydrologischen Projektionen der jährlichen und saisonalen Abflüsse zu evaluieren. Um dies zu erreichen wird das Einzugsgebiet der Thaya verwendet, welches aus den südlichen Teilen Tschechiens und den nördlichen Teilen Österreichs besteht. Die verwendeten Eichungsvarianten sind ein Blockmodell, ein gegliedertes Modell, ein flächendetailliertes Modell und ein gegliedertes Modell mit zusätzlichen Schneedaten. Die drei erstgenannten Modellarten werden für die Perioden 1986–1995, 1991–2000 und 1996–2005 geeicht, das Schneemodell für 1996–2005 und 2001–2010. Die Validierung erfolgt in Periode 2011–2019 für die tschechischen Gebiete des Einzugsgebietes und 2011–2017 für die österreichischen Gebiete. Verwendet wurden die Klimamodelle CMCC-ESM2, EC-EARTH3, GFDL-ESM4, MPI-ESM1.2-HR, MRI-ESM2.0 und TaiESM1 und die sozioökonomischen Pfade SSP 126, SSP 245, SSP 370 and SSP 585 sowie Projektionen für das Jahr 2030.

Obwohl die flächendetaillierten Modelle zu den besten Resultaten führen, zeigen alle Modelle gute Ergebnisse. Weiters können keine gebietsabhängigen Verhaltensmuster aufgrund der unterschiedlichen Höhenlagen für die benutzten Effizienzkenzahlen oder Eichungsparameter festgestellt werden.

Die hydrologischen Projektionen für SSPs 245, 373 und 585 zeigen für die saisonalen Veränderungen des Abflusses oft ähnliches Verhalten zueinander, während SSP 126 große Unterschiede aufweist. Das Klimamodell CMCC führt meist zu kleinen Verringerungen oder Vermehrungen der Abflüsse, während die anderen Klimamodelle zu signifikanten Verringerungen der saisonalen Abflüsse neigen. Die größten Verringerungen der Abflüsse finden üblicherweise von April bis Juni statt.

Über die Unsicherheiten lässt sich sagen, dass die Unterschiede zwischen den Klimamodellen zu kleineren Unsicherheiten führen als die unterschiedlichen Eichungsvarianten. Es zeigt sich hier auch, dass die Eichungsvariante mit der besten Effizienz nicht unumgänglicherweise auch zu den kleinsten Unsicherheiten führt. Wenn man die saisonalen Veränderungen der Abflüsse betrachtet, sieht man, dass die kleinsten Unsicherheiten oft im Juni auftreten. Es können keine ähnlichen konsistenten Verhaltensmuster für die größten Unsicherheiten festgestellt werden. Es gibt auch keine unumstößlichen Hinweise, welcher der SSPs zu den größten Unsicherheiten führt.

Für die jährlichen Veränderungen des Abflusses zeigen die unterschiedlichen Eichungsvarianten keine signifikanten Unterschiede für die verschiedenen SSPs und Klimamodelle.

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Glossary

$\overline{Q_{obs}}$ Longterm mean daily discharge for a given period [m^3/s].

$\overline{Q_{sim}}$ Mean of the simulated daily runoffs for a given period [m^3/s].

β Hydrological model parameter describing the non linear parameter for runoff production [-], between 0.0–20.0, parameter of TUWmodel.

$\Delta\mathbf{S}_{UZ}$ Part of rain and snow melt contributing to runoff, needed for calibration using the TUWmodel [mm].

β_1 Ratio between mean simulated and mean observed flow for the calculation of the Euclidian distance from the ideal point, used for calculating the KGE [-].

ξ_{SCA} Threshold for when catchment is snow free according to the SCA, used for the calculation of the SCAErr [%].

ξ_{SWE} Threshold for when catchment is snow free according to the SWE, used for the calculation of the SCAErr [mm].

AET Current evaporation in the area, needed for calibration using the TUWmodel [mm].

\mathbf{B}_{MAX} Hydrological model parameter describing the maximum base at low flows [days], between 0.0–30.0 days, parameter of TUWmodel.

\mathbf{B}_Q Basic duration of the transfer function, needed for calibration using the TUWmodel [day].

C Number of pixels in the picture provided by MODIS mapped as cloud, used for the calculation of the SCAErr [-].

\mathbf{C}_{perc} Hydrological model parameter describing the constant percolation rate [mm/day], between 0.0–8.0 mm/day, parameter of TUWmodel.

\mathbf{C}_{ROUTE} Hydrological model parameter describing the free scaling parameter [day^2/mm], between 0.0–50.0 day^2/mm , parameter of TUWmodel.

CESM1.2.2 Foundation of the TaiESM1 model.

CMCC-ESM2 Climate model with 30 layers and 1° horizontal resolution.

CMIP5 Coupled Model Intercomparison Project 5th phase with the aim to regulate climate simulations to guarantee global comparability, predecessor of CMIP6.

CMIP6 Coupled Model Intercomparison Project 6th phase with the aim to regulate climate simulations to guarantee global comparability, successor of CMIP5.

DDF Hydrological model parameter describing the degree day factor [mm/°C/day], between 0.0–5.0 mm/°C/day, parameter of TUWmodel.

DEoptim R package used to perform evolutionary global optimization via the Differential Evolution algorithm.

EC-Earth3 Climate model developed by EC-Earth research consortium, available with several different resolutions and number of layers.

FC Hydrological model parameter describing the field capacity, or max soil moisture storage [mm], between 0.0–600.0 mm, parameter of TUWmodel.

GFDL-ESM4.1 Climate model developed by GFDL with a resolution of 100km and 33 layers.

HBV-model Hydrologiska Byråns Vattenbalansavdelning model, commonly used hydrological model presented in the 1970s, consisting of three main moduls and basis for the TUWmodel.

k₀ Hydrological model parameter describing the storage coefficient for very fast response [days], between 0.0–2.0 days, parameter of TUWmodel.

k₁ Hydrological model parameter describing the storage coefficient for fast response [days], between 2.0–30.0 days, parameter of TUWmodel.

k₂ Hydrological model parameter describing the storage coefficient for slow response [days], between 30.0–250.0 days, parameter of TUWmodel.

I Number of zones of catchment, used for the calculation of the SCAErr [-].

L Number of pixels in the pictures provided by MODIS mapped as land, used for the calculation of the SCAErr [-].

L_{UZ} Hydrological model parameter describing the threshold storage state, or the very fast response start if exceeded [mm], between 1.0–100.0 mm, parameter of TUWmodel.

LP Hydrological model parameter describing the parameter which specifies the value of the soil moisture from which AET=PET [-], between 0.0–1.0, parameter of TUWmodel.

m Number of days with available MODIS images, used for the calculation of the SCAErr [-].

M Daily melting rate, needed for calibration using the TUWmodel [mm].

m_O Number of days were ($SWE > \xi_{SWE}$) and ($SCA = 0$), used for the calculation of the SCAErr [-].

m_U Number of days were ($SWE = 0$) and ($SCA > \xi_{SCA}$), used for the calculation of the SCAErr [-].

MPI-ESM1.2 Climate model developed at Max Planck Institute, available with several different resolutions and number of layers.

MRI-ESM1 Basis of MRI-ESM2.0 model.

MRI-CGCM3 Basis of MRI-ESM2.0 model.

MRI-ESM2.0 Climate model developed at MRI, consists of an atmosphere-ocean coupled model and has 80 vertical layers and resolution of 100km.

- n** Number of days with less than 60 % clouds, used for the calculation of the SCAErr [-].
- N** Number of days in the given period [-].
- P** Daily observed precipitation (sum of snow and rain), input for the TUWmodel [mm].
- P_R** Daily observed rainfall, needed for calibration using the TUWmodel [mm].
- P_S** Daily observed snowfall, needed for calibration using the TUWmodel [mm].
- p_{SCA}** Number of days with poor fit between SCA and SWE, used for the calculation of the SCAErr [-].
- PET** Potential evaporation in the area, input for the TUWmodel [mm].
- q₀** Fast discharge (surface runoff), needed for calibration using the TUWmodel [mm/day].
- q₁** Interflow, needed for calibration using the TUWmodel [mm/day].
- q₂** Baseflow, needed for calibration using the TUWmodel [mm/day].
- Q_G** Sum of discharges q₀, q₁ and q₂, needed for calibration using the TUWmodel [mm/day].
- Q_{obs,i}** Observed runoff at point in time i [m³/s].
- Q_{sim,i}** Simulated runoff at point in time i [m³/s].
- r, α, β₁** Three dimensions for the Pareto front for the calculation of the Euclidian distance from the ideal point, used for calculating the KGE [-].
- S** Number of pixels in the picture provided by MODIS mapped as snow, used for the calculation of the SCAErr [-].
- s₀** Potential daily sunshine duration, used for the calculation of the PET [h].
- s_i** Empirical value to consider the monthly sunshine duration, used for the calculation of the PET [-].
- s_j** Mean yearly sum of potential daily sunshine duration, used for the calculation of the PET [h].
- S_{LZ}** Storage in the lower soil layer, needed for calibration using the TUWmodel [mm].
- s_r, s_α, s_β** Scaling factors used for the calculation of the Euclidian distance from the ideal point, used for calculating the KGE [-].
- S_{UZ}** Storage in the topsoil layer, needed for calibration using the TUWmodel [mm].
- SCF** Hydrological model parameter describing the snow correction factor [-], between 0.9–1.5, parameter of TUWmodel.
- SM** Soil moisture of the topsoil layer, needed for calibration using the TUWmodel [mm].
- SM_i** Soil moisture of the topsoil layer on the day i, needed for calibration using the TUWmodel [mm].

- SM_{i-1}** Soil moisture of the topsoil layer on the day before i , needed for calibration using the TUWmodel [mm].
- SWE_i** Snow water equivalent on the day i , needed for calibration using the TUWmodel [mm].
- SWE_{i-1}** Snow water equivalent on the day before i , needed for calibration using the TUWmodel [mm].
- T** Daily observed mean temperature, input for the TUWmodel [$^{\circ}C$].
- T_M** Hydrological model parameter describing the threshold temperature above which melt starts [$^{\circ}C$], between -2.0 – 2.0 $^{\circ}C$, parameter of TUWmodel.
- T_R** Hydrological model parameter describing the threshold temperature above which precipitation is completely made out of rain [$^{\circ}C$], between 1.0 – 3.0 $^{\circ}C$, parameter of TUWmodel.
- T_S** Hydrological model parameter describing the threshold temperature below which precipitation is completely made out of snow [$^{\circ}C$], between -3.0 – 1.0 $^{\circ}C$, parameter of TUWmodel.
- TaiESM1** Climate model developed in Taiwan by the NCAR, with 30 and 60 layers and 0.9° x 1.25° and 1° horizontal resolution for land and ocean respectively.
- TUWmodel** Hydrological model developed at Technical University Vienna, based on the HBV-model and formed by three different routines.

Acronyms

ED Euclidian distance

GCM global climate model

GCMModel global circulation model

GFDL Geophysical Fluid Dynamics Laboratory

GOF goodness of fit

HR high resolution

IPCC International Panel on Climate Change

KGE Kling-Gupta efficiency

logNSE logarithmic Nash-Sutcliffe efficiency

LR low resolution

MODIS moderate resolution imaging spectroradiometer

MPE mean absolute percent error [%]

MRI Meteorological Research Institute

NCAR National Center for Atmospheric Research

NOAA National Oceanic and Atmospheric Administration

NSE Nash-Sutcliffe efficiency

OF₁ objective function 1

OF₂ objective function 2

PBIAS percent bias [%]

RCM regional climate model

RCP Representative Concentration Pathways

RMSE root mean square error

SCA snow covered area [%]

SCAErr snow covered area error [%]

SSP Shared Socioeconomic Pathway

SWE snow water equivalent [mm]

UH unit hydrograph

WCRP World Climate Research Programme

Chapter 1

Introduction

1.1 Motivation

As climate change alters many natural processes it is important to focus on understanding these changes and adapting to them. The impact can already be perceived and will only accumulate. One of the severely impacted systems is the water balance. In some cases, an increase in the amount of water can be expected, for other areas more dry periods seem to be the future norm. While the first may lead to a higher amount of floodings, loss of life and damage of critical infrastructure and housing, the second may be followed by reduced quality and quantity in drinking water, loss of crops, reduced efficiency of hydropower plants or economic damages. Either way, the water resource management needs to take these changes into account.

To be able to derive new water resource management plans reliable models are needed. But working with models leads to problems, best summarized by the following quote by Box and Draper (1987, p. 424):

"Essentially, all models are wrong, but some are useful."

Models are not the reality. They are used to depict reality in a mathematical way. However, due to the complex processes of nature, many simplifications are necessary for this depiction because of time and computing capacity. This simplification can be of advantage, as it leads to easier to understand models and faster computing times. Nevertheless, it is vital to understand the limits of a model and the included uncertainties before its usage.

There are different types of hydrological models for the assessment of discharge among other values. One of the most used types is the conceptual rainfall-runoff model. This kind of model needs to be calibrated, for which different approaches exist, for example by using different spatial processes or input data. The same model calibrated in different ways can lead to very different parameters, which results in different simulated discharges as well as different efficiency values when validating the data derived from the calibrated model with observational data.

Furthermore, the International Panel on Climate Change (IPCC) has developed various scenarios for the future, taking into account different water usages and changes in the climate. These scenarios can be applied to several climate models. The climate models and scenarios contain various uncertainties. It is impossible to predict the climate and water use definitely for 2030, even more so 2050 or 2070. Moreover, not all scenarios could become reality with the same uncertainty. Water resource management needs to be able differentiate between the various uncertainties of the scenarios in order to make useful decisions for the future.

The calibrated hydrological models can be used to run different climate models and scenarios. If the used parameters have bad efficiency values, this adds to the uncertainty of the models. Therefore, to be able to plan for the future water usage an efficient approach to the calibration is needed.

1.2 Literature overview

1.2.1 Rainfall-runoff models

1.2.1.1 History

The basis for hydrological models was developed as far back as 3000-2000 BC. Even in ancient Egypt there were attempts to predict the water levels to use them for problems related to agriculture and economy. Ancient China had the first known observations of precipitation around 1200 BC and in India the oldest precipitation measurements were found (Nace, 1974 cited in Liebscher and Mendel, 2010). Anaximander of Miletus (610 – 545 BC) was the first person to describe evaporation, which is a vital part of the water cycle in terms of cause and processes. In the following century, Anaxagoras (500-428 BC) talked about the water storage in the soil (Gabrecht, 1985 cited in Liebscher and Mendel, 2010). (Liebscher and Mendel, 2010)

During medieval times there was no new knowledge gathered about hydrology (Kresser, 1984 cited in Liebscher and Mendel, 2010).

The Renaissance from about 1500 to 1700 saw a new surge of knowledge in the field of hydrology. It started with Leonardo da Vinci (1452-1519) who engaged in research about flood risk and water shortage among many other fields of study. (Liebscher and Mendel, 2010)

The beginning of the 17th century brought upon a big change in the way natural processes were perceived. Castelli (1578-1643) rediscovered the law of continuity and was able to put it into formulas (Biswas, 1970; Dooge, 2004; Vischer, 2010 cited in Liebscher and Mendel, 2010). He was also able to formulate five axioms which stated that the discharge, which is the product of the area of the profile and the velocity, will always stay the same along a river. Castelli also was the first person to erect a precipitation measuring station in Europe. Because of that station, changes in the water level of the Trasimeno lake in Italy could be predicted. Torricelli, a student of Castelli, was able to verify the law of continuity via experiments in 1644. (Liebscher and Mendel, 2010)

The publishing of Perrault's (1611-1680) work about the water balance of a sub-catchment of the Seine in 1674 is regarded as the birth hour of hydrology (Nace, 1974 cited in Liebscher and Mendel, 2010).

Further notable insights about hydrology were Bernoulli's work about the relationship between velocity and pressure as well as the law of conservation of energy in 1738 and Euler's solution methods for partial differential equations. (Biswas, 1970 cited in Liebscher and Mendel, 2010)

The first hydrological model was designed by Mulvaney (1850) (cited in Chong-yu, 2002; Todini, 2011) and was developed to help with various engineering problems. The rational method was used for the model (Chong-yu, 2002; Todini, 2011).

In the 1920s a way to calculate bigger basins was required. The rational method was changed to be applied despite the non-uniform distribution in the larger catchments. This way the first rainfall-runoff model grounded in a transfer function was developed. (Chong-yu, 2002)

The years 1930 to 1950 saw an increase on international exchange and collaboration which led to a boost of the development of new methods. (Liebscher and Mendel, 2010)

In 1932 there was a breakthrough in the field of hydrological modelling due to the development of the unit hydrograph (UH) by Sherman. With the UH not only the peak flow was calculated, but also the volume of the hydrograph. (Chong-yu, 2002; Todini, 2011)

In the 1960s models were developed that describe each subsystem of the water cycle with conceptual interconnected components. They were considered the best solution to get additional information about the location where the response originated as well as information about the various types of responses. (Chong-yu, 2002; Todini, 2011)

After 1965 there was an effort to increase the effectiveness of rainfall-runoff models as an option to the conceptual model. One model by Freeze and Harlan (1969) (cited in Todini, 2011) used a mathematical model that is founded on distributed physical understanding of occurrences on the surface or underground. It uses partial differential equations that are split into linked sub-systems. They characterize the flow of the water on the surface and in the soil-layers, which can be either filled with water or not. The models also compare the calculations of the sub-systems to the thresholds of the other sub-systems. That way projections for the catchment can be made. (Todini, 2011)

The 1970s saw the development of a new kind of lumped model. The concept is based on the theory that the rainfall-runoff relations are mostly driven by the behaviour of saturated zones. From that a relationship to the amount of water contained in the soil can be formed using functions. The model worked under the assumption that the water from the rainfall ends up in the soil and saturates the top layer. Only after that runoff is possible. (Todini, 2011)

The last decades brought more information and data usable for modelling, like different types of soil or the utilization of the land. This led to simpler distributed models with a reduced number of parameters. (Todini, 2011)

1.2.1.2 Classification

After the small overview about the development of hydrological models in the previous chapter now a question needs to be answered: What is a model?

Stachowiak (1973) (cited in Reitzer, 1975; Ropohl, 1978) defines a model through three different characteristics:

1. A model is always a depiction of something real. The depiction is a mathematical one.
2. The depiction is not fully complete. The model will always omit details that are not necessary to fulfil the given task.
3. A model is always allotted to a certain subject, purpose and time. It is not valid in absolute terms.

When talking about rainfall-runoff models there are different ways to classify them.

Mathematical realisation

There are different approaches to the composition of the mathematical equations as can be seen below. Some may factor in statistical factors, while others are based on simpler cause-effect relationships. (Ostrowski, 2011)

- Deterministic models: As long as the input data and initial conditions stay the same a deterministic model will lead to the same results every time (Kobler, 2014). Algorithms are used to determine the solution of the simplified conceptual, empirical approaches to the equations (Ostrowski, 2011).
- Stochastic models: In a stochastic model there is an element of chance because of a statistical approach (Ostrowski, 2011). This leads to different output data, even if the same input and initial conditions are used (Kobler, 2014).

Basic structure

Rainfall leads to runoff, which is the water which stays on the surface instead of seeping into the soil. Therefore the runoff is a vital part of the water cycle. Rainfall runoff models are divided

into three different categories depending on how the correlation between rainfall and runoff is computed, as explained in the following list. Which of these types of models is chosen depends on the given tasks. (Sitterson et al., 2018)

- Empirical model (“Black Box”): In empirical models the laws of physics are ignored. Only cause-effect relations are taken into consideration. (Spektrum, 2000)

The mathematical formulas these models are based on are acquired through data series containing input and output. For the model to be correctly working they have to meet a few requirements and boundaries. (Devia et al., 2015)

Generally there is no linear connection between input and output data. One of the empirical model’s advantages is the few parameters needed for the calculations, which leads to a faster runtime of the model. However, the fact that there is no connection to the real, physical catchment is seen as a weakness. (Sitterson et al., 2018)

Empirical models are the most useful when used for ungauged areas, since the runoff is the only required output (Sitterson et al., 2018).

- Conceptual model (“Grey Box”): Conceptual models are usually only roughly based on the laws of physics and rely on empirical processes (Spektrum, 2000).

They are made up out of several reservoirs that are connected. These reservoirs are filled because of precipitation and infiltration and drained via drainage, evaporation, or runoff for example. These models need to be calibrated by using various types of meteorological or hydrological data because of the semi empirical formulas it consists of. Since the calibration works with fitting the curve of a function to measured data it is difficult to analyse the model in terms of different land uses over time. (Devia et al., 2015)

The strengths of conceptual models include the uncomplicated design of the model and the simple way to calibrate. However, the model does not take into account the spatial variability that every catchment has. (Sitterson et al., 2018)

The best use for the conceptual model is with limited time or data (Sitterson et al., 2018).

- Physical model (“White Box”): Physical models are based on the laws of physics, most of the time hydrodynamics or thermodynamics (Spektrum, 2000).

Therefore, they are, while not completely describing the real-life processes, a mathematically idealised depiction. They are functions of time and space using state variables and can be gauged. The model contains finite difference equations to model the hydrological processes like water movements. The number of needed parameters for calibration is big and many sets of data, for example soil moisture, topography or topology are needed. Since the parameters of the physical model can be interpreted physically it does not share the same problems as the other two types of models in terms of basic structure. (Devia et al., 2015)

What sets the physical model apart from other models are the fact that they include spatial and temporal variability and are available with very fine scaling. On the other side, the calibration is in need of a vast number of parameters. (Sitterson et al., 2018)

Physical models are the most efficient when much data is available on a small scale (Sitterson et al., 2018).

Spatial processes

Another way to differentiate between models is according to spatial processes as seen in figure 1.1 and the following enumeration. These processes depend on the input data and the generation of the runoff. (Sitterson et al., 2018)

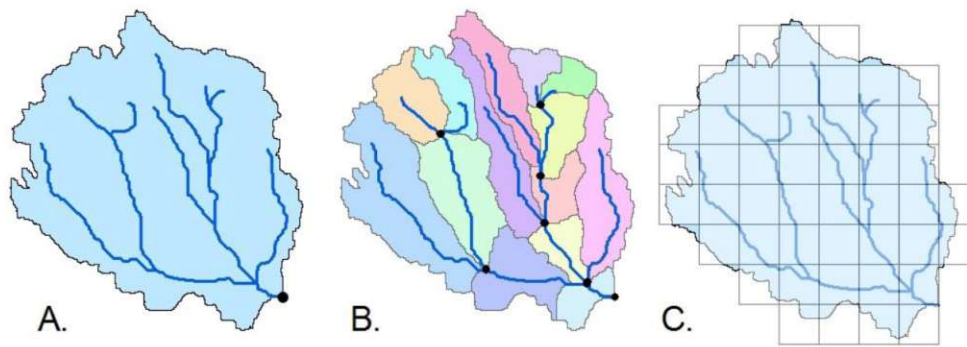


Fig. 1.1: Spatial structure in runoff models: A) Lumped model, B) Semi-distributed model, C) Distributed model. (Image taken from Sitterson et al. (2018, p. 5))

- Lumped model: The lumped model treats the whole catchment as one, without any spatial or temporal distribution. The data input is the same mean data for the whole catchment. The parameters derived from that are applied for the whole catchment. (Kobler, 2014; Sitterson et al., 2018)

One of its strengths is the comparable little time it needs for the calibration. However, the model works on a lot of assumptions, and since the spatial resolution is very high scale, it is not ideal for large areas. (Sitterson et al., 2018)

- Semi-distributed model: In semi-distributed models the catchment is split into smaller sub-catchments, or zones. Every zone has its own set of input data, however, the obtained parameters are for the whole catchment. The calculation is happening the same way as with the lumped model. (Kobler, 2014; Sitterson et al., 2018)

Because of the smaller zones there is the advantage of the vital characteristics still being taken into account. On the other hand there is a loss of spatial resolution compared to distributed models. (Sitterson et al., 2018)

- Distributed model: The spatial variability of the catchments is taken into account via geographical or statistical distribution of data input and processes in distributed models. This means that the catchment is split into zones with their own sets of input data like with the semi-distributed model. However, different parameters for each of these zones are acquired as opposite to the semi-distributed model. (Kobler, 2014; Sitterson et al., 2018)

The strengths of such an approach lies in the fact that the input is physically connected to the hydrological processes. However, much data is needed and the calculations take a long time. (Sitterson et al., 2018)

Time discretisation

There are also ways to differentiate in terms of time.

- Temporal frame:
 - Event model: They are used to depict singular events (Kobler, 2014).
 - Continuity models: If the timelines have different temporal resolutions, continuity models are used for the calculations (Kobler, 2014).
- Temporal dependance:

- Static models: The temporal change of the processes is not taken into account (Devia et al., 2015).
- Dynamic models: the temporal changes of the processes are taken into account (Devia et al., 2015).

1.2.1.3 Steps of hydrological modeling

According to Refsgaard (1997) hydrological modelling can be depicted as shown in figure 1.2, which shows that first it must be known what the model will be used for and what purpose it will serve. Then the conceptual model has to be developed and the field data gets applied. A code for the model will be picked next. After that research about already existing codes ought to be performed. If a useable one is found or a code is newly developed, the model can be designed. The performance criteria is selected in the next step. After that calibration and validation with the use of field data can be performed. With the calibrated parameters it is possible to use the model for a simulation. After the presentation of the results a post-audit can be performed to assess the effectiveness of the model with the use of field data. If the model is not performing well, a new model has to be developed for the given purpose. (Refsgaard, 1997)

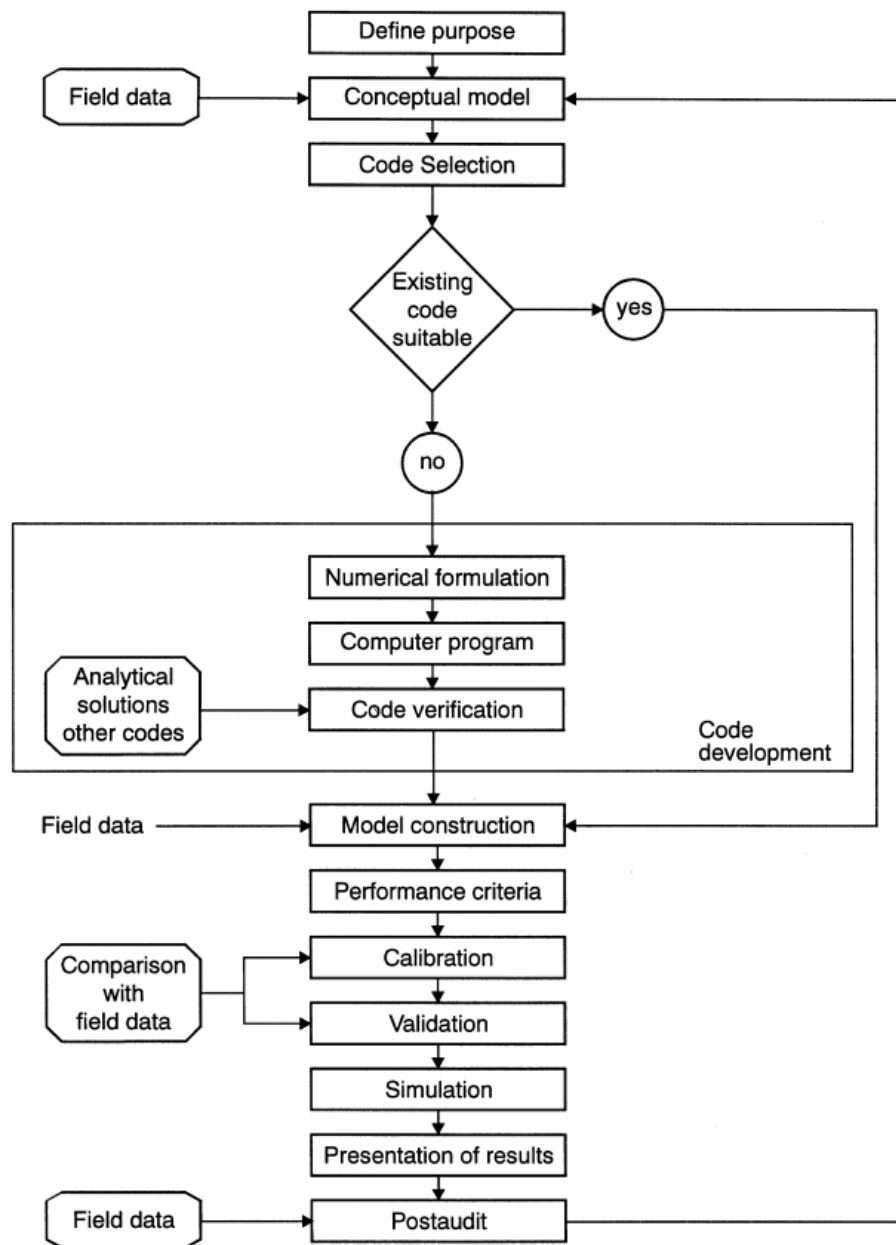


Fig. 1.2: Steps of hydrological modelling. (Image taken from Refsgaard (1997, p. 72))

1.2.1.4 Calibration

Since conceptual rainfall-runoff models rely on empirical processes, they need to be calibrated. It is non-viable to get the parameter values through tests and measurements alone. The calibration has to be performed in a way that the real life processes of the catchment are imitated and the parameter values are physically possible. (Pechlivanidis et al., 2011)

According to Yapo et al. (1996) there are several steps needed to carry out an automatic calibration:

- A set of calibration data.
- An objective function to assess the goodness of fit.

- An optimization algorithm to get to the best fitting parameters.
- A minimum and maximum value for the different parameters.
- A way to validate the calibration and to assess the uncertainty of the parameters.

Due to uncertainties in the model or the input data the results of the calibration may vary (Pechlivanidis et al., 2011).

Calibration data set

There is no consensus in literature about the required length of calibration data sets.

When looking at the change in model parameters depending on the length of the calibration period it can be seen that longer calibration periods often lead to an improvement in the parameters according to Merz et al. (2009). However, Yapo et al. (1996) conclude that a time period of more than eight years of data may not lead to significant improvements, while Merz et al. (2009) say that for some parameters the improvement due to length of the calibration period stops at approximately five years, for other parameters the improvement succeeds the five-year period. This leads to bigger uncertainties for fluxes and internal state variables (Merz et al., 2009). They may be reduced with either longer calibration periods, or different methods, like the multiple objective calibration by using for example snow data (Merz et al., 2009).

Franchini and Pacciani (1991) (cited in Wagener et al., 2004) arrive at the conclusion that the length of the calibration period and data are depending on the number of parameters that need optimisation. According to Wagener et al. (2004) a high quality data set is more important than longer calibration periods.

Multiple objective calibration

There are many studies about different types of data to utilize for model calibration. In the following paragraphs, some of them will be summarized:

- Snow data: Parajka et al. (2007) conducted a study where snow data was utilized along runoff. Since there were no obtainable snow density measurements, the snow depth data provided by stations was used to gauge the observed snow cover via daily grid maps. If the snow depth was more than 0.5 mm, the area was treated as if it was covered by snow. This was then compared to the calculated snow water equivalent. For that the threshold to be considered covered by snow was 0.1 mm. The values for the snow cover were chosen above zero to not overestimate the snow cover due to the spatial interpolation. (Parajka et al., 2007)

Another approach for using snow data for the calibration is to also incorporate the knowledge of experts about the model parameters. Instead of only applying the knowledge about the lower and upper boundary of the values there is also an attempt to estimate the distribution of the parameters. (Parajka et al., 2007)

In another study a semi-distributed hydrological model was used. Pictures of the snow cover were provided via moderate resolution imaging spectroradiometer (MODIS) and then used to calculate the snow covered area. The snow water equivalent was calculated by the model for different altitudes. Only an indirect comparison can be made because of the different units of the two values. (Parajka and Blöschl, 2008)

The snow error was also calculated. For that different thresholds for the snow covered area and the cloud cover have to be applied. (Parajka and Blöschl, 2008)

- Groundwater level data: In the paper by Seibert (2000) a HBV model was used. There were measuring stations for groundwater levels. Because of the use of the groundwater

data, the parameter values were constrained compared to the traditional calibration only using runoff. It also resulted in a more feasible depiction of the hydrology of the catchment. (Seibert, 2000)

- Soil moisture data: Wanders et al. (2014) looked into calibrating a hydrological model using both discharge data and soil moisture observations provided by satellites. The root mean square error (RMSE) was improved by 10 %–30 % compared to the traditional calibration via discharge data only (Wanders et al., 2014).

There are different ways to combine the various data sets, for example:

- Weighted sum (Parajka et al., 2007).
- Fuzzy logics: The parts of the objective function are merged according to the membership functions that show the relative level of satisfaction of the individual fuzzy objectives. Fuzzy means that the value is something between true and false. (Seibert, 1997; Parajka et al., 2007)
- Pareto optimality: If a parameter set functions on all objectives as good as the other sets, and surpasses the other parameter sets on one objective, then this set is seen as Pareto optimal. (Parajka et al., 2007)

Objective function

The most often used way for the calibration of a hydrological model is to try to change the parameters of the model in a way that the simulated runoff is as close to the observed runoff as possible (Parajka et al., 2007). For that an objective function is necessary.

The aim of the objective function is to minimize the differences between the measured and simulated data set. For that an algorithm is used (Kobler, 2014). However, Houghten-Carr (1999) concludes that in addition to the quantitative measures it is also necessary to use qualitative measures like visually comparing the flow hydrograph of the observed and simulated data.

There are different functions in use as optimization functions, for example the RMSE, mean absolute percent error [%] (MPE), Nash-Sutcliffe efficiency (NSE), logarithmic Nash-Sutcliffe efficiency (logNSE) and the Kling-Gupta efficiency (KGE) (Yu and Yang, 2000; Fowler et al., 2018). Different functions can also be applied combined in a weighted manner (Kobler, 2014).

Another approach is the so called multiple objective function. The idea is to decrease the parameter uncertainty by utilizing different kinds of data combined with the runoff data. Examples of that are snow data, groundwater level data, soil moisture and soft data. (Parajka et al., 2007)

According to Gupta et al. (2009), a multiple objectives approach is best suited for hydrological models, since the model behaviour is depending on different components in real life.

Optimization algorithm

The optimization algorithm is needed to minimize or maximize the objective function. There are different ways to optimize. In the early days of calibration it was done manually via trial and error. With time there was a change to new strategies including goodness of fit criteria and visual verification. However, a vast knowledge of the model and the catchment is needed for the manual calibration, and it is very time intensive. (Wagener et al., 2004)

If an automated optimization algorithm is used, it can be differentiated between local and global optimization (Mullen et al., 2011).

According to Sorooshian and Gupta (1995) (cited in Wagener et al., 2004) there are several reasons for problems with an automatic local calibration:

- The parameter space leads to local optima clusters.
- The response has a non-smooth surface and is not continuous because of the picked thresholds of the model.
- The parameters have a non-linear relationship.
- The global optimum is surrounded by a non-convex shape.

Because of these problems, global optimization algorithms were developed (Wagener et al., 2004).

One commonly used example of such a global optimization algorithm is the DEoptim algorithm, available as an R package (Mullen et al., 2011). It uses Differential Evolution (DE), developed by Storn and Price (1997) (cited in Mullen et al., 2011).

Minimum and maximum values

There is an upper and lower threshold for each model parameter. These thresholds are set according to individual experiences or findings of a literature research.

Terminate criterion

Different ways to terminate the iterative optimization process can be applied. If the optimization is done manually, the process is ended when the person is pleased with the model results and effectiveness (Wagener et al., 2004). According to Sorooshian and Gupta (1995) (cited in Wagener et al. (2004)) objective criteria are often used for automatic calibration as a form of measurement of the model performance and to end the process. Different kinds of objective criteria in compliance with Sorooshian and Gupta (1995) (cited in Wagener et al. (2004)) are shown in the list below:

- Function convergence: the hydrologist picks a value set as a limit for the objective function. If the objective function value is smaller, the process is terminated.
- Parameter convergence: The hydrologist picks a range for the parameters. If all parameters stay in this range for several iterations, the process is terminated.
- Maximum number of iterations: The process is terminated after a set number of iterations to avoid too long running times.

1.2.1.5 Validation

In the validation the calibrated model-parameters are tested. There are different approaches to assess the effectiveness of the calibration. One of the most used ones is the split-sample test (Arsenault et al., 2018). The datasets are split into two periods, one for calibration, one for validation (Klemeš, 1986). According to Klemeš (1986), the periods should be of equal length. If the available datasets are not long enough, then the calibration period should be picked in a way that there is enough data for a valid calibration (Klemeš, 1986). However, Klemeš (1986) does not explain why this splitting scheme is picked and there is no commonly agreed upon splitting scheme according to Liu et al. (2018).

The downside of the split sample approach is the fact that by splitting the data into two time periods for calibration and validation, there is less data available for the calibration. This means that there may be some process-characteristics in the validation period that would be needed in the calibration period for the training of the model. (Arsenault et al., 2018)

According to Refsgaard (1997), the validation process for distributed models has to be different than for lumped models. Since distributed models are usually used when there is a data

scarcity, the datasets often are not long enough for a meaningful use of the split-sample approach (Refsgaard, 1997).

Furthermore, a model should only be seen as validated for the utilization it is intended for (Refsgaard, 1997).

1.2.1.6 Uncertainty

Since a model is only a depiction of the reality, there are always differences to the real-life processes they depict. Some of these differences come to be because of uncertainties.

According to Pechlivanidis et al. (2011) there are different sources for uncertainties:

- Natural uncertainties arising from natural processes.
- Data uncertainties because of insufficient data control.
- Model parameter uncertainties due to a restricted amount of data used for calibration.
- Model structure uncertainties where the model is made up out of assumptions and observed processes and unobserved processes are not considered.

Gan et al. (1997) states that it is easier to model wet catchments compared to dry catchments. This is because of the more complicated hydrological processes (Gan et al., 1997). This means that there are also components of the catchment that influence the effectiveness of a model.

1.2.1.7 Efficiency values (goodness of fit)

The effectiveness of models needs to be verified. For that goodness of fit (GOF) values are often used. The following sections list different GOF values.

Nash-Sutcliffe efficiency

The dimensionless NSE as calculated in equations (1.1) and (1.2), developed by Nash and Sutcliffe (1970), can be used to assess the effectiveness.

$$NSE = 1 - \frac{\sum_{i=1}^N (Q_{sim,i} - Q_{obs,i})^2}{\sum_{i=1}^N (Q_{obs,i} - \overline{Q_{obs}})^2} \quad (1.1)$$

$$\overline{Q_{obs}} = \frac{1}{N} * \sum_{i=1}^N Q_{obs,i} \quad (1.2)$$

NSE ... Nash-Sutcliffe efficiency [-]

N ... number of days in period [-]

$Q_{sim,i}$... simulated runoff at point in time i [m³/s]

$Q_{obs,i}$... observed runoff at point in time i [m³/s]

$\overline{Q_{obs}}$... mean of all observed runoffs [m³/s]

The NSE is most often used when evaluating the performance of hydrological models. However, it is generally not good at gauging the efficiency of low flow conditions. It is also very responsive to peak flows. (Krause et al., 2005)

The NSE ranges from $-\infty$ to 1 and should be as close to one as possible to get a good fit. It consists of three components which characterize correlation, bias and variability. A good NSE generally means a lower estimation of the variability. (Gupta et al., 2009)

While the NSE is the most often used value to assess the GOF, it also has some well-documented problems. For example, it tends to predict less severe runoff peaks than in reality (Gupta et al.,

2009). There is also a tendency for it to be severely impacted by outliers as well as time-offset bias and bias in magnitude (McCuen et al., 2006).

When using the NSE, zero is often used as the border between a good and a bad fit in hydrological models. If the NSE is less than zero, then the mean values derived from gauging stations would lead to a better prediction than the value calculated by the model. (Moriassi et al., 2007; Knoben et al., 2019)

Gupta and Kling (2011) claim that the negative NSE indicates a problem with the balance of the masses. Moriassi et al. (2007) compare different recommendations of several studies and arrive at the conclusion that a NSE above 0.5 is adequate.

According to Engel et al. (2007) there is a difference in model performance depending on the time periods used. Shorter periods lead to worse GOF values (Engel et al., 2007). Therefore, it may be necessary to change the scale indicating good to bad fit depending on the project and time-steps.

In Oudin et al. (2006) there was an attempt to counteract the low performance with low flow conditions. A logarithmic approach was applied to the NSE.

Percent Bias

Another way to assess the GOF is the percent bias [%] (PBIAS) as shown in (1.3).

$$PBIAS = 100 * \frac{\sum_{i=1}^N (Q_{sim,i} - Q_{obs,i})}{\sum_{i=1}^N (Q_{obs,i})} \quad (1.3)$$

PBIAS ... percent bias [%]

N ... number of days in period [-]

$Q_{sim,i}$... simulated runoff at point in time i [m³/s]

$Q_{obs,i}$... observed runoff at point in time i [m³/s]

The PBIAS assesses if the output of the model is an overestimation or underestimation of the reality. It should be as close to zero as possible, as zero indicates no differences between simulation and observation. (Zambrano-Bigiarini, n.d.)

Moriassi et al. (2007) compared different recommendations and arrived at the conclusion that a PBIAS of ± 25 % is adequate for discharge.

Kling-Gupta efficiency

Equations (1.4), (1.5) and (1.6) and figure 1.3 show the calculation of the KGE in accordance to Gupta et al. (2009, p. 83).

$$KGE = 1 - ED \quad (1.4)$$

$$ED = \sqrt{[(s_r * (r - 1))^2 + [s_\alpha * (\alpha - 1)]^2 + [s_\beta * (\beta_1 - 1)]^2} \quad (1.5)$$

$$\beta_1 = \frac{\overline{Q_{sim}}}{\overline{Q_{obs}}} \quad (1.6)$$

KGE ... Kling-Gupta efficiency [-]

ED ... Euclidian distance from the ideal point

s_r, s_α, s_β ... scaling factors

r, α, β_1 ... three dimensions

$\overline{\beta_1}$... ratio between mean simulated and mean observed flow

$\overline{Q_{sim}}$... mean of all simulated runoffs [m³/s]

$\overline{Q_{obs}}$... mean of all observed runoffs [m^3/s]

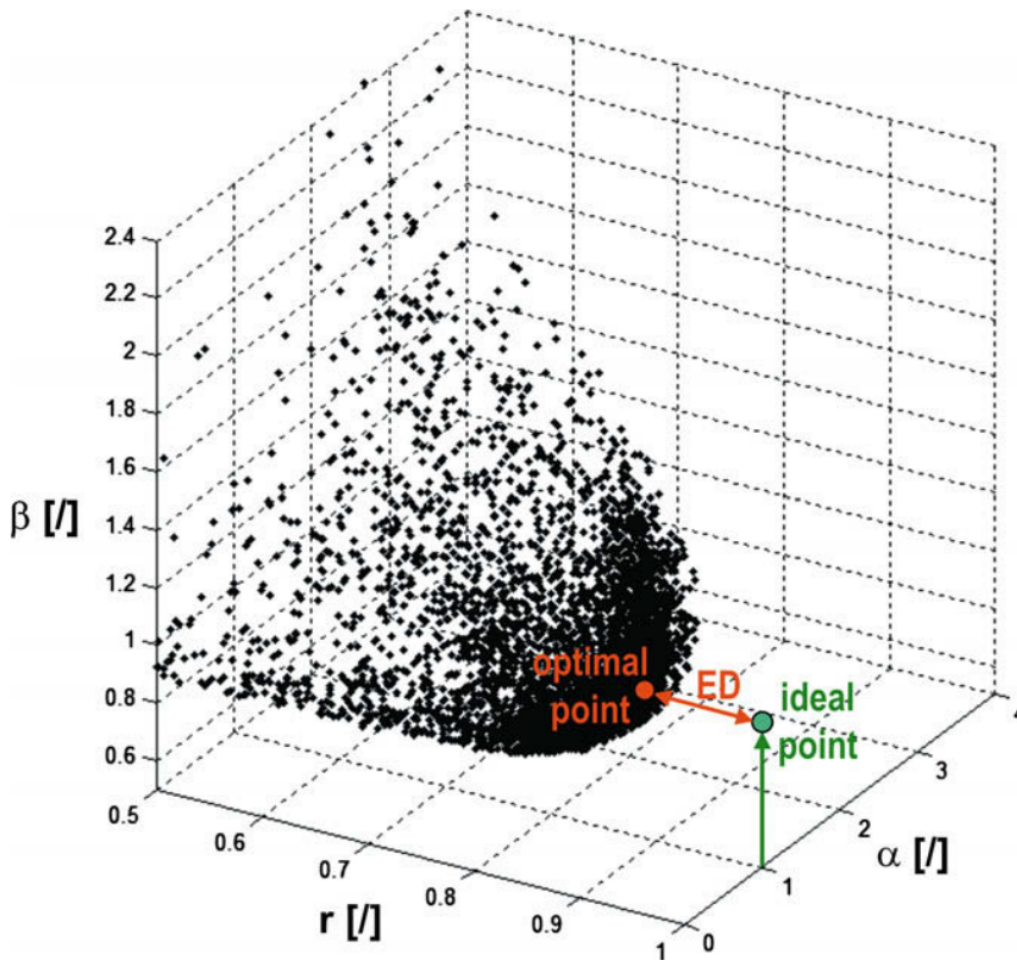


Fig. 1.3: Example for three dimensional Pareto front. (Image taken from Gupta et al. (2009, p. 83))

The KGE was developed during a study which aims to decompose the NSE and for a better performance in the NSEs problem areas (Gupta et al., 2009). It consists of the same three parameters as the NSE, but with different weightings (Liu, 2020). The KGE has a new set of performance difficulties (Gupta et al., 2009). However, it tends to predict runoff peaks more reliable than the NSE (Gupta et al., 2009). According to Knoben et al. (2019) the KGE should not be assessed the same way as the NSE. If the mean observation is used as border for the goodness of fit, then a KGE bigger than $1-\sqrt{2}$ should be considered a good fit. (Knoben et al., 2019)

Snow Covered Area Error

The snow covered area error [%] (SCAErr) can be calculated according to the following equations (1.7), (1.8) and (1.9) in accordance with Parajka and Blöschl (2008, p. 244). There are two errors, the overestimation error shown in equation (1.7), and the underestimation error shown in equation (1.8). (Parajka and Blöschl, 2008)

$$SCAErr^O = \frac{1}{m * l} \sum_{i=1}^l m_O \quad (1.7)$$

$$SCAErr^U = \frac{1}{m * l} \sum_{i=1}^l m_U \quad (1.8)$$

$$SCA = \frac{S}{S + L} \quad (1.9)$$

$SCAErr^O$... Overestimated snow covered area error [-]

$SCAErr^U$... Underestimated snow covered area error [-]

m_O ... number of days were ($SWE > \xi_{SWE}$) and ($SCA = 0$) [-]

m_U ... number of days were ($SWE = 0$) and ($SCA > \xi_{SCA}$) [-]

m ... number of days with available MODIS images [-]

l ... number of zones of catchment [-]

ξ_{SWE} ... threshold for when catchment is snow free according to the SWE [mm]

ξ_{SCA} ... threshold for when catchment is snow free according to the SCA [%]

SWE ... Simulated snow water [mm]

SCA ... Snow covered area [%]

S ... number of pixels mapped as snow [-]

L ... number of pixels mapped as land [-]

It is a more grievous mistake in the estimation to show snow, although no snow was detected via MODIS for example, or to show no snow, although MODIS shows snow, compared to differences in the estimated snow depths. Because of that the SCAErr is the percentage of days with less than 60% clouds in the given picture, when only one out of the model or the observation shows snow, but not the other. However, because of errors in the model thresholds for when detected or simulated snow is counted as snow cover have to be implemented. (Parajka and Blöschl, 2008)

1.2.1.8 Performance of different types of models

There have been many studies conducted about the performance of different types of models in terms of spatial processes concerning their calibration. The following paragraphs aim to give an overview of the most important findings.

Lumped vs Semi-distributed

In the study performed by de Lavenne et al. (2016) it is shown that the model performance of the lumped model usually leads to better fitting statistical criteria for the calibration period as well as the validation period compared to the semi-distributed model. It is also pointed out that semi-distributed models should not only be assessed via GOF values. The parameter identifiability should also be looked into. That way the model can be better applied to investigate future scenarios or catchments without gauging stations. (de Lavenne et al., 2016)

In Garavaglia et al. (2017) the semi-distributed model performs notably better than the traditional lumped model when simulating the runoff and is able to simulate snow processes close to real-life observations.

Lumped vs Distributed

Reed et al. (2004) show that lumped models usually have a better performance than distributed models. This may be more due to the modeler's abilities, the parametrization or the model itself, not due to if the model is lumped or distributed. (Reed et al., 2004)

According to Pokhrel and Gupta (2011) the calibration of distributed models will not yield useful outcomes without minimizing structural errors and data errors till they are smaller than hydrograph variations due to spatial variability.

Semi-distributed vs Distributed

El-Nasr et al. (2005) compare two different models, one semi-distributed, one distributed. Both simulations are adequate, however the distributed model is a little bit better at capturing the variation of the river flow. The distributed model further is able to depict the moderate extreme values, whereas the semi-distributed model is better at depicting the peaks. (El-Nasr et al., 2005)

Calibration with additional snow data

The approach via snow cover in addition to the discharge generally yields good results for the calculation of the snow cover (Parajka et al., 2007). However, the estimation of the runoff is slightly worse than with the conventional method using only the runoff data, according to Parajka et al. (2007).

When applying snow data as well as expertise to further narrow down the values the parameters can take on the calculated runoff for the calibration period for this approach is comparable to the conventional method. The results for the validation period show an increased efficiency. Since the weighting scheme is different than in the method without the experts knowledge, the snow cover model is less efficient when using the additional expertise. (Parajka et al., 2007)

For the study conducted by Parajka and Blöschl (2008) it can be said that the runoff calculated via MODIS and runoff data for the calibration is generally close to the runoff calculated only with the conventional method. The calibration using snow data performs better than in the conventional method. (Parajka and Blöschl, 2008)

Parajka and Blöschl (2008) furthermore claim that the method using data provided by MODIS generally leads to better results in small areas with limited measuring stations during the calibration period. However there is still room for improvement in the resolution of the satellite sensors. (Parajka and Blöschl, 2008)

The runoff also shows a better efficiency during the validation period when using MODIS data. However, there may be a decrease in performance when using a shorter period. (Parajka and Blöschl, 2008)

Furthermore Sleziak et al. (2017) claim that the use of snow data for the model calibration leads to an increase in effectiveness for the snow components of the model, but not so much for the other parameters.

Udnæs et al. (2007) conclude that using discharge data and SCA data in the calibration leads to similar simulations for discharge, but better simulated SCA.

1.2.2 Climate change modeling

1.2.2.1 Mechanisms of climate change

In the last few decades an increase in air temperature and a change in the precipitation was noticed globally. The impact of these changes in climate differs depending on region, for example the air temperature increased more in the alpine regions than the global mean temperature increase. (Schimon et al., 2011)

When looking at a reconstruction of the timely changes of the energy provided by the sun it can be seen that until a few decades ago the climate changes were brought upon mainly by the energy of the sun and the cooling effects of volcanoes. However, in the last few decades anthropogenic processes were the cause of a rise of the so-called greenhouse gases, a term for emissions like CO₂,

CH₄ and N₂O among others. These emissions lead to an increase in temperature. (Schimon et al., 2011)

The impacts of these emissions were however “masked” in the first years after the second World War. Because of the technologies of the time aerosols were released into the air, which have a cooling effect on the climate, like volcanoes. After implementing technology to keep the air clean, this cooling effect stopped, but the greenhouse gases remained. (Schimon et al., 2011)

There are trends in the development of the air temperature, however they may change depending on the region. The alpine regions have different changes than coastal areas for example. The mean annual precipitation also has trends, depending on the region. However, shorter time resolution leads to conflicting data due to the available data quality. Floods, while easier to measure, also do not have a specific trend. (Blöschl and Montanari, 2010)

1.2.2.2 Types of climate change models

There are two types of climate change models: global climate models (GCMs) and regional climate models (RCMs).

GCM

The climate system consists of four crucial parts: atmosphere, land surface, ocean and sea ice. These four components are interlinked. A GCM is a mathematical depiction of the four components. (GFDL, n.d.)

RCM

A RCM aims to give information about regional and local changes to the climate (Rummukainen, 2010). To do that a GCM has to be scaled down (Rummukainen, 2016). They have higher resolutions and provide additional value to the findings of GCMs (Feser et al., 2011; Rummukainen, 2016).

1.2.2.3 Steps for modeling climate change

According to Blöschl and Montanari (2010) and Schimon et al. (2011) the following steps are needed to assess possible future changes in the climate:

- After looking at the future economy predictions and the global circulation model (GCMModel) one or more of the climate change scenarios of the International Panel on Climate Change (IPCC) are chosen.
- The GCMModel output has to be adjusted for the scale of catchment the assessment is for.
- Then the GCMModel output is used as input for a hydrological model. The model can now make simulations for the future climate.
- The model is also used to simulate for the current climate. The two simulations can now be compared.

The GCMModel is needed because of the influence the air and sea circulation have on the climate. The circulation of the sea is much slower than the air circulation, but even after a few weeks an interaction between the two can be seen. (Haimberger et al., 2014)

Furthermore, climate models are not a statistical extrapolation of past data. The future is modelled via the laws of physics, which also depicts feedback loops. (Haimberger et al., 2014)

1.2.2.4 Uncertainty

According to (IPCC, 2007) most of Earth's water resources are anticipated to go through a net negative impact due to climate change. However, there is a difference in the severity and how exactly the resources are affected depending on the region. While some regions can be expected to go through droughts because of the climate change and an increase in water demand, other regions can expect floodings, be it a temporary or a permanent rise of the sea level. This will lead to agricultural and economic problems like a decrease in crop yield. (Abbaspour et al., 2009)

To understand the severity of the problems it is important to know about the uncertainties of climate models and to use different scenarios to gauge the full range of climate change effects (Arnell et al., 2004). Furthermore, if the climate projections are similar for different simulations, they are more likely to come true. It is easier for regions with similar projections to plan for the future of the water resource management.

When trying to run a model for the changing climate, every step of the modelling will add a new source of uncertainties. One source of uncertainties is the scaling. Bigger scales lead to bigger errors in the numeric solutions. Newer generations of models have smaller scales due to a higher computing capacity. (Haimberger et al., 2014)

Other uncertainties are related to the exchange of warmth, vapor and substances between the atmosphere and surfaces as well as aerosols and their processes (Haimberger et al., 2014). Also mistakes of the modeller, for example in the code of the model, are always a possibility (Haimberger et al., 2014). Another source of uncertainties is because of the hydrological model parameters and emission scenarios (Wilby and Harris, 2006).

Generally, climate models are relying on laws of physics and well-used numeric solutions, but due to a lack of knowledge about the relevant processes and needed simplifications there will always be uncertainties (Haimberger et al., 2014).

Because of these uncertainties it is important to gauge the reliability of the models. This can be done via different methods. For once, the past can be simulated with the model and compared to observations. Another method is to use ensemble-calculations. Ensemble-calculations are trying to model the same task, but in different ways. For example, they use different models, different parameters, or they differ in initial conditions. (Haimberger et al., 2014)

1.2.2.5 Modelling impacts of climate change on water resources

Water resource management is needed to link different disciplines of hydrology and to plan, manage and utilize water resources effectively to satisfy the needs of the population. However, due to changes in the climate, the population and the consumption the quantity and quality of water resources will change. To assess these changes, guarantee a reliable supply and be able to plan for the future a model of the water resources is needed. (Rehana et al., 2020)

To be able to model the water resource management on a regional level several different kinds of models are needed as seen in the following list according to Rehana et al. (2020):

- a hydrological model to gauge the accessibility of water.
- a water quantity and quality estimation model to understand when water should be released from reservoirs and what treatments are necessary for the water.
- a water demand estimation model to approximate the amount of water needed for drinking, watering and hydropower.
- a decision making model.

These models also contain a number of uncertainties, stemming from a lack of quality or errors in the data, inaccuracies in the model, insufficient knowledge of the modeller, arbitrary changes of nature, variability of operations and overall inaccuracies. (Rehana et al., 2020)

Furthermore, the water resource models are only as valid as the used climate models (Varis et al., 2004). Usually, GCMs are either directly used or downscaled for the given purposes (Varis et al., 2004). However, there are still many unresolved questions about climate change processes, which lead to unsatisfying model performances (Kundzewicz and Stakhiv, 2010). So it can be seen that there is a need for gaining more understanding about the different modelling dynamics of climate models.

Climate change leads to changes in hydrological processes like infiltration, evapotranspiration and soil moisture. According to Peel and Blöschl (2011) further research about the reaction of the hydrological processes to change is needed. This can be done via climate models. However, these models need calibration parameters with satisfying efficiencies to be able to predict future climates.

Merz et al. (2011) calibrated the parameters of a conceptual rainfall-runoff model to several consecutive time periods for Austrian catchments. They were able to show that the parameters representing snow and soil moisture have different trends when calibrated for different time periods. Since these trends are alike for different zones in the catchment, it can be assumed that they are real trends, and not just due to the calibration process. (Merz et al., 2011)

Duethmann et al. (2020) take a look at the HBV model and its inability to simulate the difference of the discharges due to the gauged change in precipitation and air temperature because of climate change. They attribute the problems with the simulation to two points: The used model does not take differences in the vegetation dynamics and heterogeneities of the precipitation data into account. These problems could not be counteracted by prolonging the calibration period by twenty years, making changes to the objective function to include snow data or annual discharge data, or using a different method to approximate the evaporation did not change the outcome significantly. (Duethmann et al., 2020)

This leads to the assumption that caution is needed when calibrated parameters are used for climate predictions. There may be more model uncertainties compared to the usual uncertainties. However, avoiding calibration would also mean that the bias reduction calibration provides would not happen. Therefore the need for further research on the impacts of the different forms of calibration on the various uncertainties of climate projections arises. (Merz et al., 2011)

1.3 Research objectives of the thesis

The aim of this thesis is to examine and evaluate the uncertainty of hydrological projections because of different calibration strategies. This is done by investigating the performance and uncertainties of lumped, semi-distributed and distributed calibration variants as well as a multi-objective calibration approach in the Thaya catchment.

There are three goals of this thesis:

1. Compare four calibration variants of a conceptual hydrological model for different calibration periods in terms of efficiency. This includes a lumped, semi-distributed and distributed approach as well as a semi-distributed model with additional snow data .
2. Assess the projections of mean annual and seasonal discharge in the Thaya basin based on six different climate scenarios representing four shared socio economic pathways.
3. Evaluate the uncertainty of hydrological projections of annual and seasonal discharges.

The uncertainties are evaluated via comparison of the different outputs of the climate models.

Chapter 2

Methods

2.1 Hydrological model

2.1.1 TUWmodel

For this thesis a version of the TUWmodel implemented in R has been used. It was developed from the HBV-model (Hydrologiska Byråns Vattenbalansavdelning), a model first presented in the 1970s in Sweden. It now has been used in over 30 countries. It is implemented as a semi-distributed model and uses simple structures for the simulation of the runoff processes. The HBV-model consists of three main modules to take into account the snow accumulation and snow melt, the soil moisture and the runoff. (Bergström, 1992)

Model structure

The TUWmodel is a conceptual hydrologic model and is used in its lumped, semi-distributed and distributed variants in this thesis. Model inputs are the precipitation, air temperature and potential evaporation. There are three different routines and 15 parameters that need to be calibrated as can be seen in figure 2.1 below. In this thesis the used model outputs are discharge and snow water equivalent for each of the catchments. (Valent, 2022; Parajka et al., 2023c)

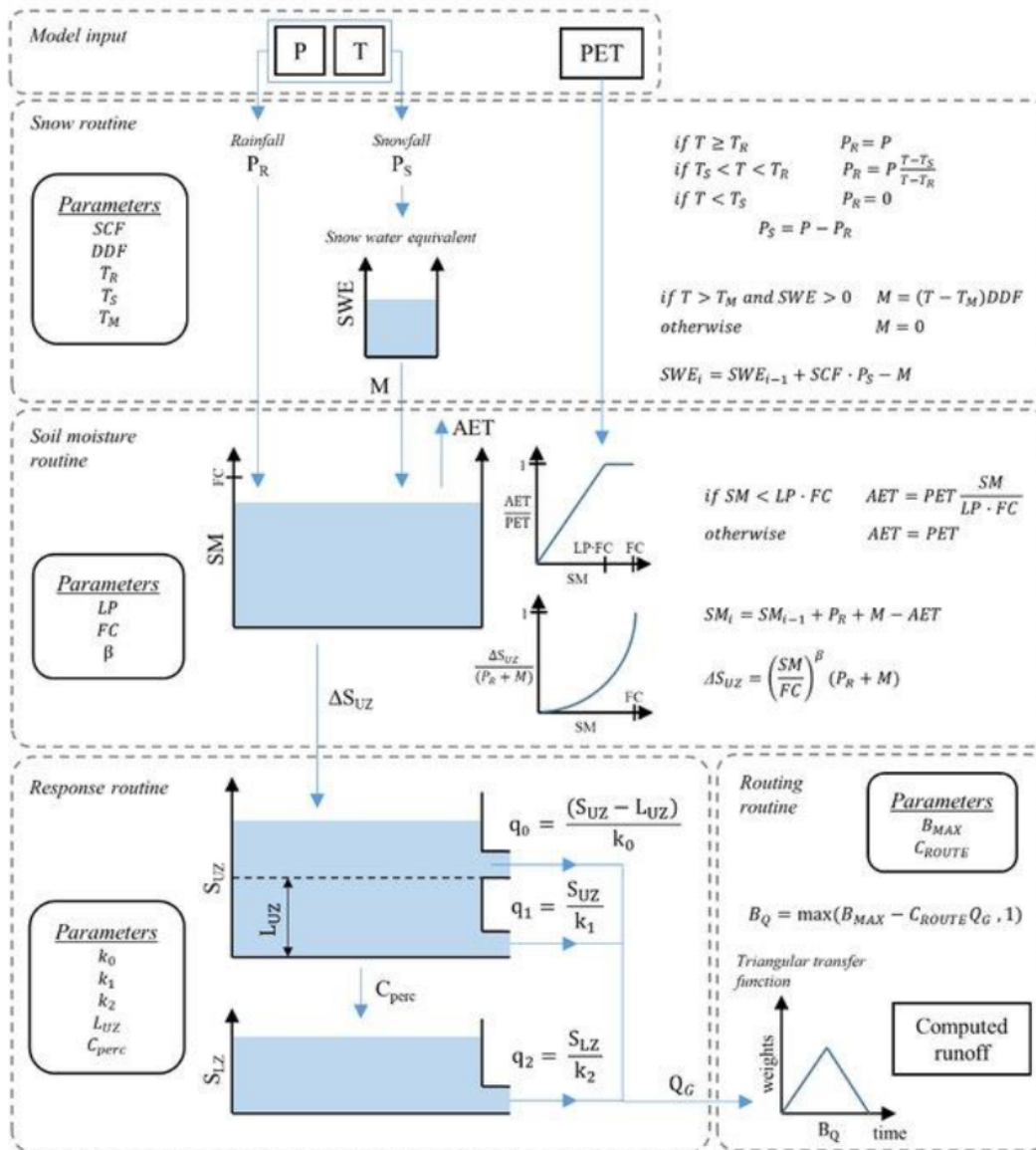


Fig. 2.1: TUVmodel structure. (Image taken from Valent (2022, p. 11))

The TUVmodel is available as a package for R. (Viglione and Parajka, 2020; Parajka et al., 2023b) The R software is an open source software (Parajka et al., 2023c). In this thesis the chosen timestep is one day.

The equations (2.1) - (2.10) in the following section are taken from Valent (2022, p. 11).

Snow routine

The snow routine estimates snow accumulation and the melting of snow via degree-day method and includes the parameters SCF , DDF , T_M , T_S and T_R (Valent, 2022).

The snow accumulation gauges the aggregate condition of the precipitation as can be seen in equation (2.1) derived from Valent (2022). For that a function for the daily mean temperature T is defined. If the temperature is lower than T_S the whole precipitation is made out of snow, if it is higher than T_R the whole precipitation consists of rain. (Parajka et al., 2005; Valent, 2022)

$$P_S = P - P_R \text{ mit } P_R = \begin{cases} P & \text{if } T \geq T_R \\ P * \frac{T - T_S}{T - T_R} & \text{if } T_S < T < T_R \\ 0 & \text{if } T \leq T_S \end{cases} \quad (2.1)$$

P ... daily observed precipitation (sum of snow and rain) [mm]

P_S ... daily observed snowfall [mm]

P_R ... daily observed rainfall [mm]

T ... daily observed mean temperature [°C]

T_S ... threshold temperature below which precipitation is completely made out of snow [°C]

T_R ... threshold temperature above which precipitation is completely made out of rain [°C]

The snow melt is calculated via degree-day method as can be seen in the equation (2.2). Here the temperature T_M is the start of the snow melt and M is the daily melting rate. (Parajka et al., 2005; Valent, 2022)

$$M = \begin{cases} (T - T_M) * DDF & \text{if } T > T_M \text{ and } SWE > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2.2)$$

M ... daily melting rate [mm]

T ... daily observed mean temperature [°C]

T_M ... threshold temperature above which melt starts [°C]

DDF ... degree day factor [mm/°C/day]

SWE ... snow water equivalent [mm]

Equation (2.3) shows how the difference of the snow water equivalent for each time step is calculated. In this case the chosen time step is one day. The snow correction factor SCF is needed due to errors in the measurements of the snow precipitation. (Parajka et al., 2005; Valent, 2022)

$$SWE_i = SWE_{i-1} + SCF * P_S - M \quad (2.3)$$

SWE_i ... snow water equivalent on day i [mm]

SWE_{i-1} ... snow water equivalent on the day before i [mm]

SCF ... snow correction factor [-]

P_S ... daily observed snowfall [mm]

M ... daily melting rate [mm]

Soil moisture routine

The soil moisture routine describes the soil moisture in the topsoil layer SM as can be seen in equation (2.4). Here AET is the current evaporation of the area and is calculated as shown in equation (2.5). To calculate AET the topsoil SM, the potential evaporation PET and the parameters LP and FC are needed. LP describes the soil moisture at which the current evaporation AET is the same as the potential evaporation PET. FC is the maximum storage capacity in the topsoil layer. (Parajka et al., 2005; Valent, 2022)

$$SM_i = SM_{i-1} + P_R + M - AET \quad (2.4)$$

$$AET = \begin{cases} PET * \frac{SM}{LP*FC} & \text{if } SM < LP * FC \\ PET & \text{otherwise} \end{cases} \quad (2.5)$$

SM_i ... soil moisture of the topsoil layer on the day i [mm]

SM_{i-1} ... soil moisture of the topsoil layer on the day before i [mm]

P_R ... daily observed rainfall [mm]

M ... daily melting rate [mm]

AET ... current evaporation in the area [mm]

PET ... potential evaporation in the area [mm]

LP ... parameter which specifies the value of the soil moisture from which $AET=PET$ [-]

FC ... field capacity, or max soil moisture storage [mm]

Then the part of rain and snow melt that contributes to the runoff is calculated. The equation (2.6) is a non-linear function of SM and requires the maximum storage capacity in the topsoil layer FC and the measure of the non-linearity of the discharge formation β for the calculation. (Parajka et al., 2005; Valent, 2022)

$SM=FC$ would mean the complete saturation of the topsoil layer, which means the whole rain and snow melt is a part of the runoff. On the other hand $SM<FC$ means there is a partial saturation and rain and snow melt cause a higher saturation in the topsoil layer. The amount of moisture in the top soil layer can only be decreased through evaporation. (Parajka et al., 2005; Valent, 2022)

$$\Delta S_{UZ} = \left(\frac{SM}{FC} \right)^\beta * (P_R + M) \quad (2.6)$$

ΔS_{UZ} ... part of rain and snow melt contributing to runoff [mm]

SM ... soil moisture of the topsoil layer [mm]

FC ... field capacity, or max soil moisture storage [mm]

β ... non linear parameter for runoff production [-]

P_R ... daily observed rainfall [mm]

M ... daily melting rate [mm]

Response routine

The generated produced hillslope runoff and stream routing is estimated in the response routine. There are two reservoirs. They stand for the runoff routine on the hillslopes. The precipitation that does not get held back in the soil moisture routine accumulates to the storage in the topsoil layer S_{UZ} . There are three ways to leave the upper reservoir: via outflow according to the k_1 storage coefficient (which is associated with the interflow q_1), percolation via the constant percolation rate C_{perc} , or via outflow based on the very fast storage coefficient k_0 (which is linked to the fast discharge or surface runoff q_0), if the storage state threshold L_{UZ} is surpassed. The lower reservoir S_{LZ} is emptied proportional to its contents due to the slow storage coefficient k_2 (which is connected to the the base flow of the groundwater storage q_2). This can all be seen in equations (2.7) - (2.9). (Parajka et al., 2005; Valent, 2022; Parajka et al., 2023c)

$$q_0 = \frac{(S_{UZ} - L_{UZ})}{k_0} \quad (2.7)$$

$$q_1 = \frac{S_{UZ}}{k_1} \quad (2.8)$$

$$q_2 = \frac{S_{LZ}}{k_2} \quad (2.9)$$

- q_0 ... fast discharge (surface runoff) [mm/day]
- q_1 ... interflow [mm/day]
- q_2 ... base flow [mm/day]
- k_0 ... storage coefficient for very fast response [days]
- k_1 ... storage coefficient for fast response [days]
- k_2 ... storage coefficient for slow response [days]
- S_{UZ} ... storage in the topsoil layer [mm]
- L_{UZ} ... threshold storage state, or the very fast response start if exceeded [mm]
- S_{LZ} ... storage in the lower soil layer [mm]

The outflow of the two reservoirs then passes a triangular transfer function, which stands for the runoff routing in streams with the parameters B_{MAX} and C_{ROUTE} and the discharge Q_G . B_{MAX} represents the highest base at low flows and C_{ROUTE} is regarded as a free scaling parameter. Q_G is the sum of q_0 , q_1 and q_2 . (Valent, 2022; Parajka et al., 2023c)

The following equation (2.10) captures the described processes:

$$B_Q = \max \left\{ \begin{array}{l} B_{MAX} - C_{ROUTE} * Q_G \\ 1 \end{array} \right. \quad (2.10)$$

- B_Q ... basic duration of the transfer function [day]
- B_{MAX} ... maximum base at low flows [day]
- C_{ROUTE} ... free scaling parameter [day²/mm]
- Q_G ... sum of discharges q_0 , q_1 and q_2 [mm/day]

2.2 Model calibration and validation

2.2.1 Calibration and validation

Lumped model

The input for the objective function differs depending on the used spatial processes. For the lumped model input is used and the calculations are done for the whole catchment. The model parameters are valid for the whole catchment.

Semi-distributed model

The semi-distributed model splits the catchment into smaller zones for which input data is provided. The difference between the zones and catchments can be seen in figure 2.2 below.

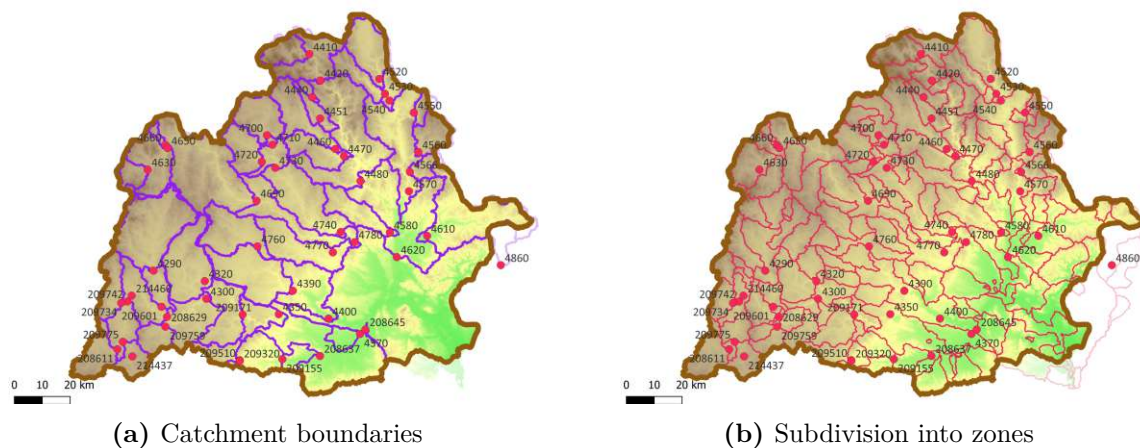


Fig. 2.2: Thaya region. Catchment (left) and zone (right) boundaries.

There are minor changes in the code for the input data due to the change in input. Matrices were used instead of vectors for temperature, precipitation and potential evaporation. However, no individual model parameters for the zones are calibrated.

The sum of the area of the zones of one catchment is not the same as the area of the catchment for which the information about the gauging stations was provided by the Interreg study. However, the difference between the area of the zones and the real area of the catchment would lead to negligible differences in the calibration. For the smaller catchments only one zone was provided, so it is decided that the parameters and statistical values from the lumped model is used for them and no new calibration is necessary.

Snow model

The snow model uses the same zones as the semi-distributed model. However, the objective function is expanded to also include snow data for the zones.

Distributed model

For the distributed model the data for air temperature, precipitation and solar index for the different zones is used to calibrate different parameters for each zone. The discharge data is still available for the whole catchment. Because of numerical problems with the optimization algorithm, the distributed model in this thesis is modified. For every head-catchment the parameters calibrated in the semi-distributed model for the given time period are entered. In the following catchments down the river, only the parameters for the new zones are calibrated. The parameters of the zones of the catchments upstream are kept the same.

The order of the calibration can be seen in figure 2.3 below. Depending on the period there is not enough data for some of these catchments. If that is the case, they are skipped both during calibration and as input of parameters for the next catchment. Moreover, some catchments contain the exact same zones as the one before them, so they do not need new calibration.

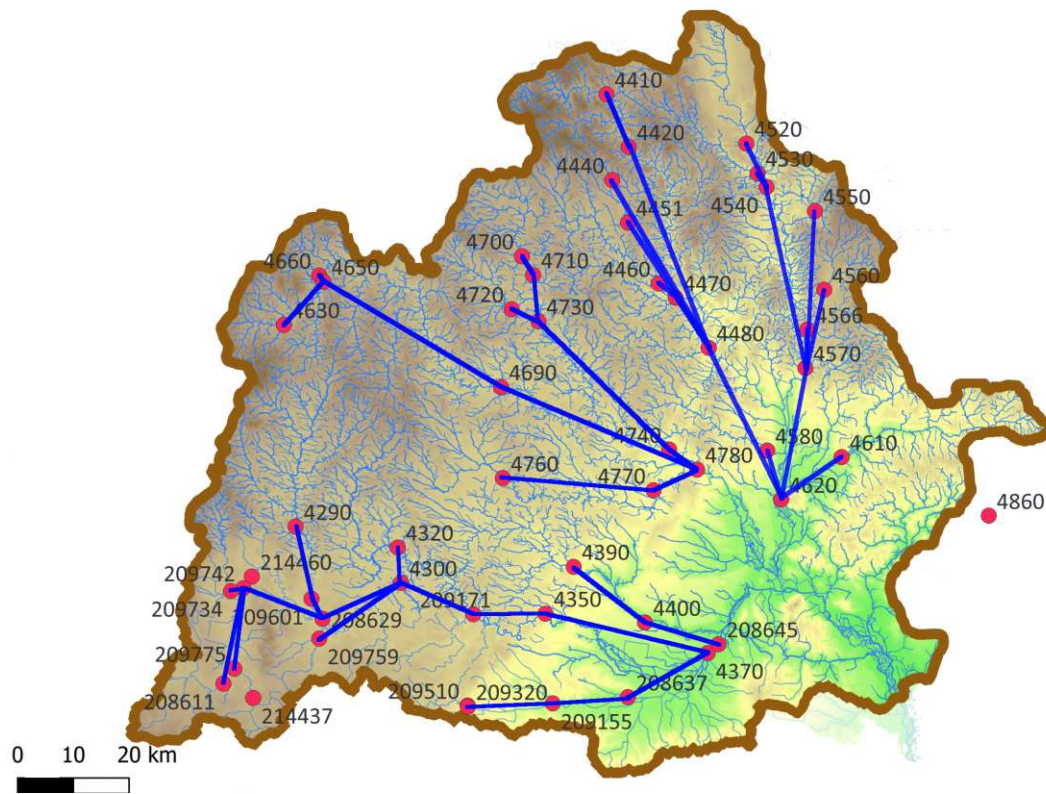


Fig. 2.3: Calibration order for distributed model

Calibration

For the calibration an automatic calibration is chosen instead of a manual one because of the number of catchments in need of calibration. The automatic calibration is carried out using the optimization algorithm of the DEoptim package by Mullen et al. (2011). For the termination criterion a relative convergence tolerance of $1e^{-4}$ and a steplength of 50 are chosen. This means that the optimization algorithm is ended when the value of the objective function has not been reduced by more than the factor 10^{-4} in the last 50 iteration steps. If the calibration reaches 600 iterations it is terminated independently of that due to time constraints.

There are four different periods used for the calibration: 1986–1995, 1991–2000, 1996–2005 and 2001–2010. The first three periods are used for the calibration of the lumped, semi-distributed and distributed model. They are chosen according to the available data sets. For the snow model the periods 1996–2005 and 2001–2010 are used because MODIS data needed for the calibration is only available from the 25.02.2000 onwards. The first four years of period 1996–2005 still have to be calculated without snow data.

The values the parameters can assume in the calibration as well as their units can be seen in Tab. 2.1 below.

Tab. 2.1: Ranges of TUWmodel parameters used in model calibration.

Parameters	Unit	Lower threshold	Upper threshold
SCF	[-]	0.9	1.5
DDF	[mm/°C/day]	0.0	5.0
T_M	[°C]	-2.0	2.0
T_R	[°C]	1.0	3.0
T_S	[°C]	-3.0	1.0
LP	[-]	0.0	1.0
FC	[mm]	0.0	600.0
β	[-]	0.0	20.0
k_0	[days]	0.0	2.0
k_1	[days]	2.0	30.0
k_2	[days]	30.0	250.0
C_{perc}	[mm/day]	0.0	8.0
LUZ	[mm]	1.0	100.0
B_{MAX}	[days]	0.0	30.0
C_{ROUTE}	[day ² /mm]	0.0	50.0

Validation

A split sample approach is chosen to validate the model. There are differences in the chosen validation period depending on the origin of the data. The validation period for the Czech catchments is 2011–2019, for the Austrian catchments 2011–2017 due to data scarcity. The validation of all models also includes MODIS snow data.

The calibrated and validated parameters need to be evaluated concerning their efficiencies. To do that the R package hydroGOF is installed. It contains different performance metrics. There is no ideal performance metric for all catchments and conditions, different performance metrics have different application areas (Krause et al., 2005; Waseem et al., 2017).

The used GOF values can be seen below. The equations used are as shown in equations 1.1 - 1.9 in chapter 1.2.1.7.

- NSE
- logNSE
- PBIAS
- KGE
- SCAErr

There are also diagrams made to be able to visually compare simulated and observed discharge on a monthly basis as well as depending on the input data daily basis for both calibration and validation. The SCA and SWE are also illustrated as diagrams for the periods MODIS data was available for as a form of further visual control.

2.2.2 Objective function

There are two different objective functions in use. The first is a combination of the NSE and the logNSE for the lumped, semi-distributed and distributed model. The second also incorporates the SCAErr into the objective function for the snow model.

Objective function 1: combination of NSE and logNSE

As first objective function a mixture of the NSE and the logNSE is used as can be seen in equations 2.11 - 2.15. This is because of the fact that the use of the NSE is widely spread in the area of rainfall-runoff modelling. Furthermore previous experiences in Austrian projects also show the effectiveness of the value (Parajka et al., 2023c). With the combination of both NSE and logNSE high and low flow conditions are both taken into account (Parajka et al., 2023c).

$$NSE = 1 - \frac{\sum_{i=1}^N (Q_{sim,i} - Q_{obs,i})^2}{\sum_{i=1}^N (Q_{obs,i} - \overline{Q_{obs}})^2} \quad (2.11)$$

$$\overline{Q_{obs}} = \frac{1}{N} * \sum_{i=1}^N Q_{obs,i} \quad (2.12)$$

$$\logNSE = 1 - \frac{\sum_{i=1}^N (\log Q_{sim,i} - \log Q_{obs,i})^2}{\sum_{i=1}^N (\log Q_{obs,i} - \log \overline{Q_{obs}})^2} \quad (2.13)$$

$$\log \overline{Q_{obs}} = \frac{1}{N} * \sum_{i=1}^N \log Q_{obs,i} \quad (2.14)$$

$$OF_1 = - \left(\frac{NSE}{2} + \frac{\logNSE}{2} \right) \quad (2.15)$$

OF₁ ... objective function 1

NSE ... Nash-Sutcliffe efficiency [-]

logNSE ... logarithmic Nash-Sutcliffe efficiency [-]

N ... number of days in period [-]

$Q_{sim,i}$... simulated runoff at point in time i [m³/s]

$Q_{obs,i}$... observed runoff at point in time i [m³/s]

$\overline{Q_{obs}}$... longterm mean daily discharge for a given period [m³/s]

Objective function 2: combination of NSE, logNSE and SCAErr

For the snow model the SCAErr is also incorporated into the objective function. Objective function 1 gets extended as can be seen in equations 2.16 - 2.18 to also include the SWE calculated by the TUWmodel and the SCA. To get the SCA, the amount of pixels containing snow, clouds or ground captured daily by MODIS is used. If more than 60 % of the picture consists of clouds, there is not enough data available and the day is not used. If less than 40 % of the picture are clouds, the percentage of snow-pixels out of the area covered by snow or ground is calculated. This procedure is in accordance with Parajka and Blöschl (2008). The thresholds for detecting snow in the SCA is set for under 0.1 % of pixels that show snow to count as no snow in the whole area and for over 5 % of pixels designated as snow to count as snow in the area. For the SWE the thresholds under 0.1 mm for no snow and over 1 mm for snow are chosen.

The formulas for the NSE and logNSE stay the same.

$$p_{SCA} = \sum_{i=1}^N \left\{ \begin{array}{ll} 1 + SCA & \text{if } SCA > 0.05 \text{ and } SWE < 0.1 \\ 1 + \frac{SWE}{10} & \text{if } SCA < 0.001 \text{ and } SWE > 1.0 \end{array} \right. \quad \text{if } \frac{C}{S + L + C} < 60 \% \quad (2.16)$$

$$SCAErr = \frac{p_{SCA}}{n} \quad (2.17)$$

$$OF_2 = 0.5 * (1 + OF_1) + 0.5 * SCAErr \quad (2.18)$$

OF₁ ... objective function 1

OF₂ ... objective function 2

SCAErr ... snow covered area error [%]

SCA ... snow covered area [%]

SWE ... snow water equivalent [mm]

C ... number of pixels mapped as cloud [-]

L ... number of pixels mapped as land [-]

S ... number of pixels mapped as snow [-]

N ... number of days in period [-]

p_{SCA} ... number of days with poor fit between SCA and SWE [-]

n ... number of days with less than 60 % clouds [-]

2.3 Hydrological projections

In Riahi and Krey (2023) different scenarios for the years 2030, 2050 and 2090 were developed. In this thesis the calibrated model parameters are used to run climate models with different scenarios for the year 2030. The parameters for the different spatial processes and calibration periods are entered as well as the input data from the potential evaporation. The precipitation and temperature data is derived from the different climate models (see more about them in chapter 3.3.2). All this data is used to run the TUWmodel. Afterwards the discharges from the different climate models and calibration periods are compared to each other in order to get to know the uncertainties of the scenarios.

2.4 Uncertainty analysis

Model efficiency of different calibration variants

For the analysis of the efficiency of the model calibration the medians and variability of the GOF values for the calibration and validation for all calibration variants are looked at and compared. The variability describes the range of GOF values that are calculated due to the different calibration variants. This is done for monthly efficiency as well as daily efficiency.

Then the average of NSE, logNSE and KGE is calculated for calibration and validation for monthly and daily efficiency each to be able to better compare the different variants. The average NSE, logNSE and KGE as well as PBIAS and SCAErr when available are then looked at to determine the most effective calibration variant.

After that the behaviour of the subcatchments of two different calibration variants is compared to see if trends and patterns can be detected. Then the parameter values are analysed first via median values and variability throughout the catchments and then via spatial variability to see if patterns can be established.

Hydrological projections

The changes in discharge for the different climate models and SSP scenarios are compared for the most effective calibration variant. This is done in comparison to a 30 year historical period and a 10 year historical period for seasonal changes and for a 30 year period for annual changes.

Uncertainty of hydrological projections

The projections for changes in discharge for the different calibration variants are compared for different climate models and SSP scenarios. This is done for seasonal changes in comparison to a 30 year historical period and a 10 year historical period as well as for annual changes in a 30 year period. Furthermore, the range of changes for calibration variants and climate models is discussed.

Chapter 3

Data

3.1 Study region

The model area consists of the Thaya basin which has an area of 13.419 km² (Fischer et al., 2023). 13 % of the basin consists of the northern parts of Austria and 83 % of the southern parts of the Czech Republic (Fischer et al., 2023). It includes 53 catchments of both countries, 15 from Austria and 37 from Czechia. Their sizes are between 19.8 and 3938 km² (Parajka et al., 2023b). The area of each catchment as well as their location can be seen in the attachment in table 6.1.

The Austrian part of the Thaya catchment is located at approximately 676 m a.s.l, while the Czech part of the Thaya basin, or Dyje basin as it is called in Czechia, is located at 635 m a.s.l. (Fischer et al., 2023).

In terms of altitude higher parts of the catchment consist of crystalline bedrocks, the lower reaches are formed out of quaternary sediments. Approximately 66 % of the area is used for crops, while 28 % is made up of forests. In the middle and lower parts of the catchments the Thaya includes human made alterations, reservoirs for example. (Fischer et al., 2023)

The southeastern part of the Czechian share of the catchment contains several state natural reserves and NATURA 2000 reserves and features vast biodiversity. However, there is no larger protected area. (Miklín and Hradecký, 2016)

3.2 Hydrological data

The data used in this thesis is provided by the Interreg study (see Parajka et al. (2023b), Parajka et al. (2023c), Parajka et al. (2023a) and Parajka et al. (2023d)). The data sets are not only determined for the Thaya basin, but also for adjacent areas (Parajka et al., 2023b). The quality of the data sets has been evaluated and cross-checked by the parties involved in the study (Parajka et al., 2023b).

There are two kinds of precipitation, temperature and evapotranspiration input data used in this thesis. The first one for the lumped model, where the data is entered for the whole catchment, the second one for the other three models (semi-distributed, snow and distributed model), which are in need of separate data for each zone.

3.2.1 Discharge

For the calculations 52 gauging stations in the Thaya basin for the observation of daily discharge are used as can be seen below in figure 3.1. 37 are located in the Czech Republic, 15 in Austria. The area of the measured basins for discharge varies between 19.8 to 3938m² (Parajka et al., 2023b).

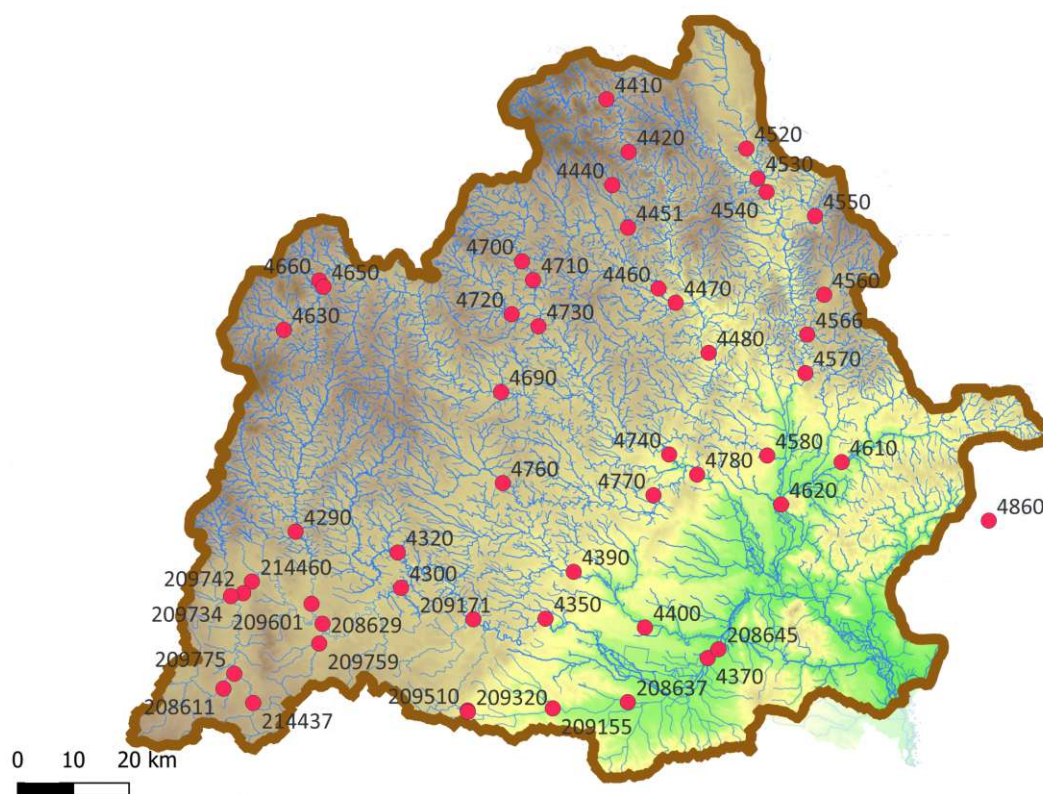


Fig. 3.1: Location of discharge gauging stations

While the stations of the Czech Republic have data ranging from 1961 to 2019, the amount of data from Austria's stations varies. All but one have the same ending date on 31.12.2017, but different starting dates.

Because of that depending on the chosen period there is a different amount of Austrian catchments available for the calibration:

- 1986–1995: 7 catchments
- 1991–2000: 8 catchments
- 1996–2005: 10 catchments
- 2001–2010: 12 catchments

Since there is only data available until 31.12.2017 for Austrian catchments, the validation period is two years shorter than for the Czech catchments.

For some of the catchments naturalized discharge data is available. See chapter 3.3.1 for more information.

3.2.2 Precipitation

262 measuring stations are used for the measurement of the precipitation in the Thaya catchment. 137 of these stations are located in the Czech Republic, 125 in Austria. They are placed in altitudes from 153 to 737 m a. s. l. and can be seen in figure 3.2 below. The precipitation data has been provided assigned to each catchment or zone by the Interreg study. (Parajka et al., 2023b)

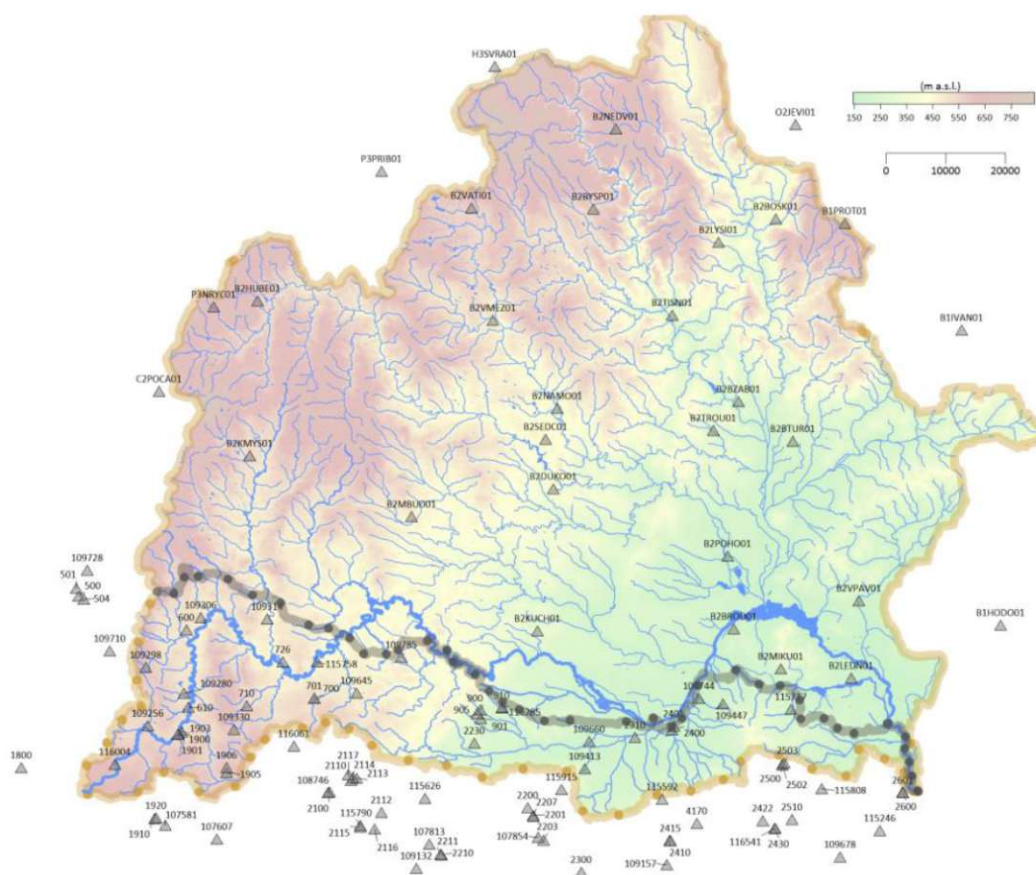


Fig. 3.3: Location of air temperature gauging stations. (Image taken from Parajka et al. (2023b, p. 9))

The air temperature data from 01.01.1986 to 31.12.2019 is used in this thesis.

3.2.4 Potential evaporation

56 stations for other climate data like sunshine duration, wind speed and relative air humidity are used. 30 of them are located in the Czech Republic, 26 in Austria as can be seen in figure 3.4. (Parajka et al., 2023b)

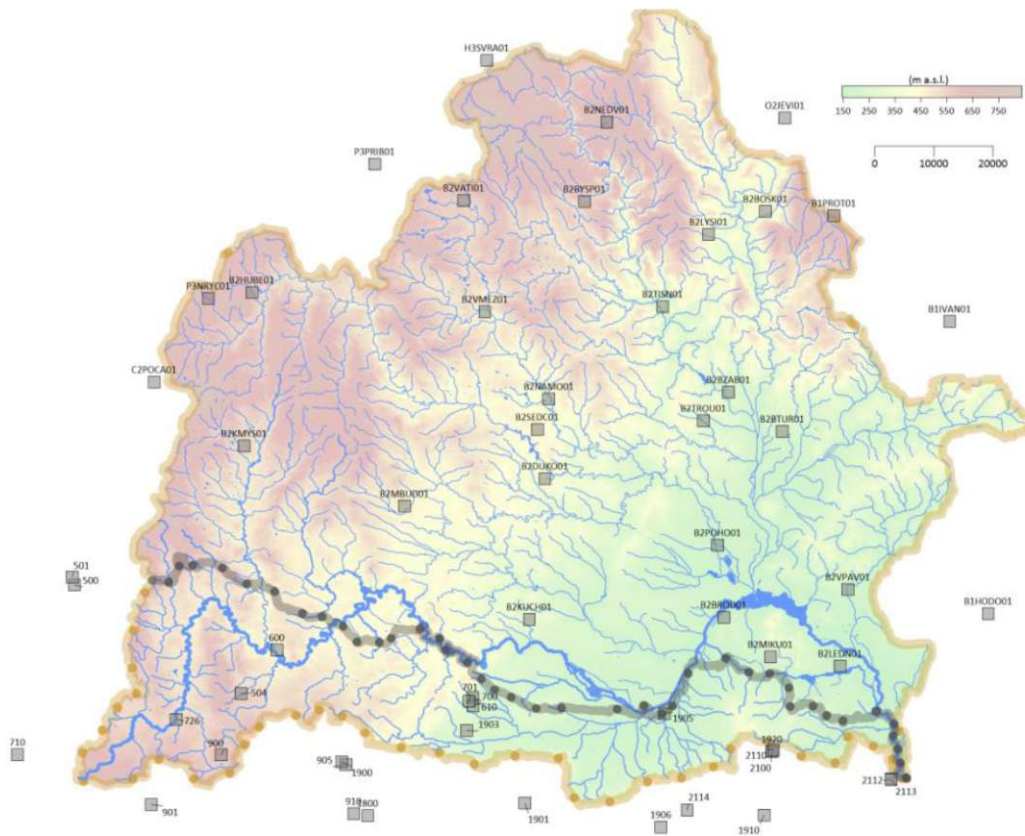


Fig. 3.4: Location of other climate gauging stations. (Image taken from Parajka et al. (2023b, p. 10))

The potential evaporation is calculated using the modified empirical Blaney-Criddle equation according to Parajka et al. (2003) as can be seen in equations (3.1) and (3.2). Temperature data and the solar index derived from the sunshine duration are needed for the calculation. There are 12 values for the solar index available for every catchment or zone, one for each month.

$$PET = -1.55 + 0.96 * (8.128 + 0.457 * T) * \underbrace{\frac{s_0 * 100}{s_j}}_{s_{i,i}} \quad (3.1)$$

$$s_i = \begin{pmatrix} s_{i,Jan} \\ s_{i,Feb} \\ s_{i,Mar} \\ s_{i,Apr} \\ s_{i,May} \\ s_{i,Jun} \\ s_{i,Jul} \\ s_{i,Aug} \\ s_{i,Sep} \\ s_{i,Oct} \\ s_{i,Nov} \\ s_{i,Dec} \end{pmatrix} \quad (3.2)$$

- PET ... potential evaporation [mm/day]
 T ... daily observed mean temperature [°C]
 s_0 ... potential daily sunshine duration [h]
 s_j ... mean yearly sum of potential daily sunshine duration [h]
 s_i ... empirical value to consider the monthly sunshine duration [-]

3.2.5 MODIS

The Moderate-Resolution Imaging Spectroradiometer, or MODIS for short, is a mission from NASA. It achieves world-wide pictures with a resolution of 250 m from the year 2000 onwards. (NSIDC, n.d.)

There are two types of satellites fitted with MODIS, Aqua and Terra. Terra progresses by the equator north to south in the morning, Aqua south to north in the afternoon. That way, Terra and Aqua together are able to survey the whole surface of the Earth approximately every 1 or 2 days. (NASA, n.d.)

MODIS provides pictures of the Earth. From these pictures the number of pixels representing land, snow or clouds are derived and used for calibration or validation.

The MODIS data has been provided for each zone for the period 25.02.2000 to 31.12.2020. The data is captured daily via MOD10A1 in a 500m resolution. Version 6.1 has been used.

3.3 Climate projections

3.3.1 Water use

The measured discharge values are impacted by human processes due to water utilization. The discharges would be higher without anthropogenic influences like water use for drinking, agriculture or economy for example. Since the Interreg study required the available amount of water used for different processes, some of the discharge data accounts for the human usage of water and is naturalized. For that different kinds of information have to be applied. (Parajka et al., 2023b)

Data about the past application of the water of the Thaya basin has been accumulated. However, the data from the Czech Republic is generally more detailed and time consistent than the Austrian data. (Parajka et al., 2023b)

The amount of used water from the Thaya basin is much smaller in Austria than in the Czech Republic. This is explained by the smaller area and fewer access possibilities in Austria. There are, however, hardly any recordings about the water usage in Austria aside from special situations, so the legal consensus has to be used instead. The legal consensus is the maximum amount of water that is legally allowed to be extracted by the user. From experience it can be assumed that it is not used to the fullest. Usually the use is at approximately 50 % depending on the kind of application. The amount of used water often differs depending on what it is utilized for. The demand for drinking water usually does not change abruptly, while in agriculture the need for water often depends on the type of plants and the climate amongst other things. (Parajka et al., 2023b)

In the Czech Republic the Decree No. 431/2001 Coll. controls the surveillance of the information about groundwater and surface water use as well as the discharged water. The information includes extractions from 500 m³/month or 6000 m³/year upwards, as well as data about what the water is used for among other things. It contains information from 1979 onwards.

It can be seen that in recent years less surface water has been extracted, while the groundwater use and the amount of discharged water have risen. (Parajka et al., 2023b)

With the help of the monthly data from the Czech Republic the percentage distribution over the different sectors throughout the year were generated. With that the monthly water management values for Austria could be estimated. (Parajka et al., 2023b)

With this additional data it is possible to naturalize some of the available discharges.

To develop future scenarios for the water use, it is vital to estimate the change in demography. According to Parajka et al. (2023b) the Czech Statistcal Office (CSO 2014, 2013) released projections of the change in population for the Czech Republic. It is estimated that in 2030 about 9.1 to 10.9 million people and in 2050 about 8.4 to 11.0 million people will live in the Czech Republic. This would mean a decrease or a slight increase in population, even when accounting for immigration. (Parajka et al., 2023b)

For Austria the relevant districts for the Thaya basin are Waldviertel and Weinviertel. According to Parajka et al. (2023b) the province of Lower Austria, Department of Spatial Planning and Regional Policy Statistics has published the “Bevölkerung-PrognosePlus_20172032”. In this report it is stated that the changes in population are linear with an increase of the population in the Weinviertel to 51877 by 2050 and a decrease in the Waldviertel to 29826 by 2050. (Parajka et al., 2023b)

3.3.2 Climate models

For this thesis data of different climate models is used with the calibrated parameters in order to gauge their uncertainties. The models are all a part of the CMIP6 project of the World Climate Research Programme (WCRP). This project aims to regulate climate simulations to guarantee global comparability. (Lawrence Livermore National Laboratory, 2019; Legutke et al., 2012)

- **MRI-ESM2.0:** The MRI-ESM2.0 model developed at Meteorological Research Institute (MRI) builds upon the MRI-CGCM3 and MRI-ESM1 models, which participated in CMIP5, the predecessor of CMIP6. The model consists of an atmosphere-ocean coupled model. It is linked to interactive models for atmospheric chemistry and aerosols. With its 80 vertical layers the model improves on the 48 layers of its predecessors. The horizontal resolution for atmospheric and oceanic parts is 100 km. (Yukimoto et al., 2019)

The MRI-ESM2.0 shows a reasonable representation of both the average climate as well as the interannual variability. However, there are still areas in need of improvement. (Yukimoto et al., 2019)

- **MPI-ESM1.2:** As the latest update to the Max Planck Institute climate models, the MPI-ESM1.2 model aims to refine the physical processes representation as well as the calculations, applications and user friendliness. (Mauritsen et al., 2019)

The MPI-ESM1.2 model is available as both high resolution (HR) and low resolution (LR). The differences can be seen in the table 3.1 below. (Mauritsen et al., 2019)

Tab. 3.1: Differences in resolution for MPI-ESM1.2 according to Mauritsen et al. (2019)

Resolution	Atmospheric grid spacing [km]	Atmospheric vertical levels	Oceanic grid spacing [km]	Oceanic vertical levels
LR	200	47	150	40
HR	100	95	40	40

To put it in a nutshell, the HR version of this model is better used to simulate the atmospheric mean state and regional atmospheric processes than the LR version. The HR application leads generally to useful predictions and impact studies. (Müller et al., 2018)

- GFDL-ESM4.1: The National Oceanic and Atmospheric Administration (NOAA)'s Geophysical Fluid Dynamics Laboratory (GFDL) has produced a new kind of AM4.0/LM4.0 atmosphere/ land model. It is the foundation for another kind of climate and Earth system models (CM4 and ESM4). The horizontal resolution is approximately 100 km, the vertical resolution 33 levels. (Zhao et al., 2018)

The GFDL-ESM4.1 model is able to reproduce the most important regional historical climate characteristics according to Dunne et al. (2020).

- EC-Earth3: The EC-Earth3 model is the third version of this model developed by the EC-Earth research consortium. There are different resolutions and configurations available (Döscher et al., 2022):
 - Standard resolution: 80 km
 - Low resolution: 125 km
 - High resolution: 40 km

There are also different numbers of vertical levels depending on the configuration, for example:

- Configuration AerChem: 34 levels
- Configuration CC: 10 levels

Döscher et al. (2022) state that the EC-Earth3 model simulates physical behaviour and biases adequately.

- CMCC-ESM2: The CMCC-ESM2 model is the second version of the CMCC Earth System Model. It consists of 30 layers and has a horizontal resolution of 1°. (Lovato et al., 2022)
- The models simulations of the physical climate and biosphere processes for the present are satisfactory. When simulating global warming signal and carbon accumulation for different future scenarios the findings are comparable with other models. (Lovato et al., 2022)
- TaiESM1: TaiESM1 uses the CESM1.2.2, developed by the National Center for Atmospheric Research (NCAR) as foundation (Lee et al., 2020).

For the horizontal resolution on land and in the atmosphere grids with $0.9^\circ \times 1.25^\circ$ are used. There are 30 layers. The oceanic part of the model has a roughly 1° resolution and consists of 60 layers. (Lee et al., 2020)

The data of the climate models MRI-ESM2.0, MPI-ESM1.2-HR, GFDL-ESM4, EC-EARTH3, CMCC-ESM2 ad TaiESM1 is available for 2030, which means the period from 01.01.2015 to 30.12.2044. In this thesis the data for the average temperature and the rain is used for each zone. It has been provided by the Institute of Hydraulic Engineering and Water Resources Management of the TU Wien.

In the following chapters the models are referred to as:

- CMCC-ESM2: CMCC
- EC-EARTH3: EC

- GFDL-ESM4: GFDL
- MPI-ESM1.2-HR: MPI
- MRI-ESM2.0: MRI
- TaiESM1: TAI

3.3.3 Future scenarios

Several future climate scenarios have been developed by an international team consisting of climate scientists, economists and energy system modellers. These scenarios are called Shared Socioeconomic Pathways (SSPs). In essence the scenarios describe pathways for the future of the Earth considering the development of population, economy, education, urbanisation and technology. (Hausfather, 2018)

According to Hausfather (2018) and Böttinger and Kasang (n.d.) there are five different SSP narratives, which can be seen in figure 3.5 as well as the following list:

- SSP1: This is the sustainable and green pathway. Its priority is the well-being of humanity instead of economic growth. Global resources are used cautiously. There is an emphasis on the well-being of nature and responsible use of resources as well as cooperation between countries.
- SSP2: It describes the middle way. On that pathway the previous developments are continued. While the state of nature generally worsens, the increase in population slows down after 2050. There is still somewhat of a cooperation between different countries.
- SSP3: In some areas there are severe damages to nature. Because of nationalism and regional conflicts global problems are ignored. Politicians start caring foremost about security. Because of these developments, education and development of new technologies are ignored.
- SSP4: Environmental problems are only addressed on the regional level, to varying degrees of success. Inequality is prevalent. There are growing differences between developed, cooperating communities and communities with lower level of education and income.
- SSP5: Here a focus on fossil fuels is prevalent. Because of an energy intensive lifestyle on a global scale more fossil fuels are needed. New technologies and innovations are developed also with the use of fossil fuels.

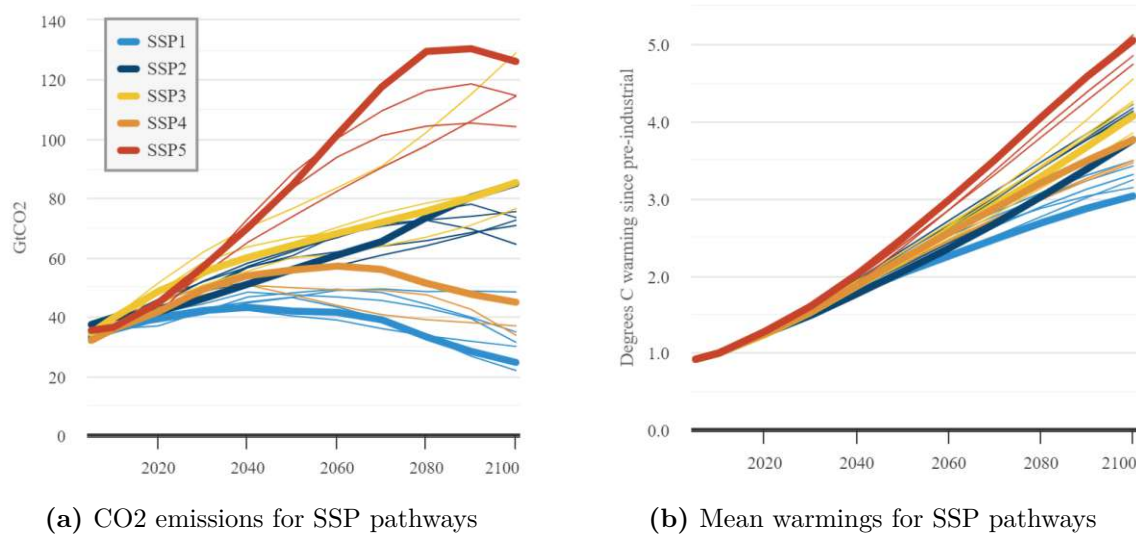


Fig. 3.5: Impact of different SSP pathways on CO₂ emissions and mean temperature. (Image taken from Hausfather (2018))

The SSPs can be linked with the Representative Concentration Pathways (RCP), which do not consider socioeconomic inputs. They provide information about the various levels of greenhouse gases and radiative forcings that may come about after some time. There are different RCP pathways until 2100, as can be seen in figure 3.6 as well as the list below: (Hausfather, 2018)

- RCP 2.6: It is believed that in this scenario the global warming will stay under 2°C (IPCC, n.d.). There is also the expectation that after 2100 there will be constant net negative emissions (Climatewatch, n.d.).
- RCP 4.5: In this scenario, the radiative forcing will not surpass 4.5 W/m² after 2100 (Thomson et al., 2011). The maximum of the emissions will be reached by 2040, after which there will be a decrease (Cal-Adapt, n.d.).
- RCP 6.0: This scenario predicts only a slight increase in emissions (Zomer et al., 2015).
- RCP 7.0: It is a comparatively new scenario to bridge the gap between scenarios 6.0 and 8.5 (Hausfather, 2018).
- RCP 8.5: The highest baseline emissions will be yielded due to this scenario, because of an increase of the emissions throughout the 2000s (Cal-Adapt, n.d.).

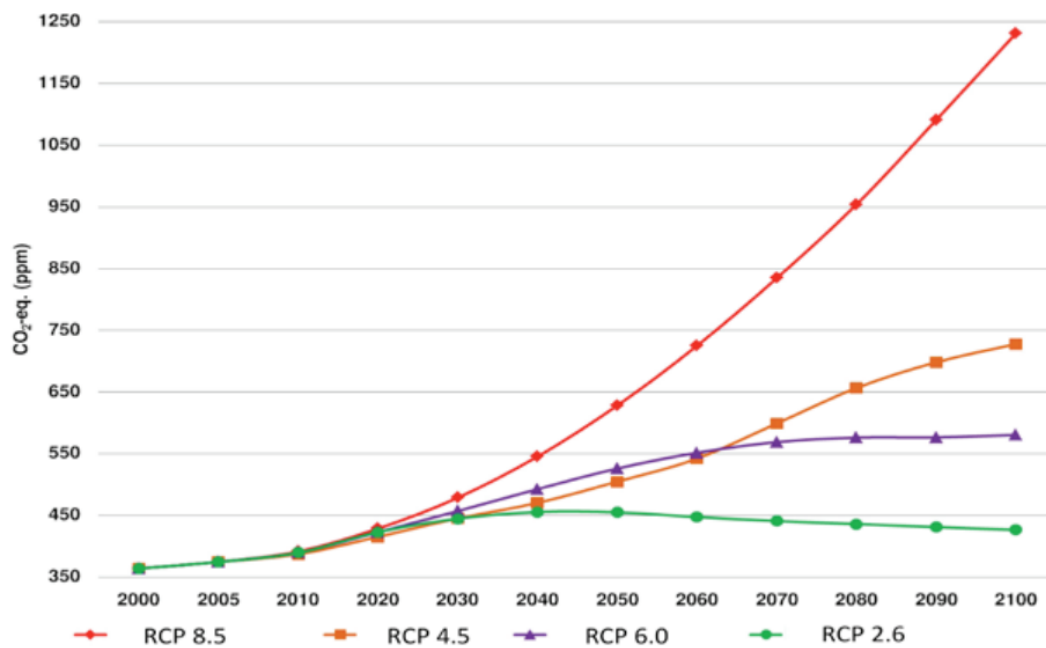


Fig. 3.6: Impact of different RCP pathways on CO₂ equivalent. (Image taken from Zomer et al. (2015, p. 6))

In this thesis the following scenarios are chosen for the year 2030 in compliance with the combinations according to the global agreement stated in Böttinger and Kasang (n.d.):

- SSP 1 with RCP 2.6, further referred to as SSP 126
- SSP 3 with RCP 7.0, further referred to as SSP 370
- SSP5 with RCP 8.5, further referred to as SSP 585
- SSP2 with RCP 4.5, further referred to as SSP 245

Chapter 4

Results

4.1 Model efficiency of different calibration variants

The following subsections contain the findings for the model calibration. For further information on the GOF and parameter values please see the diagrams and tables in chapters 6.2.1 and 6.2.2.

The GOF values only include the catchments calibrated with the respective calibration variant. This means that the catchments with only one zone for the semi-distributed variants and the headcatchments for the distributed variants are not considered in the calculation of the GOF.

4.1.1 Calibration model efficiency

Monthly runoff efficiency in calibration period

The following paragraphs discuss the findings for the GOF values for monthly data, as can be seen in figure 4.1.

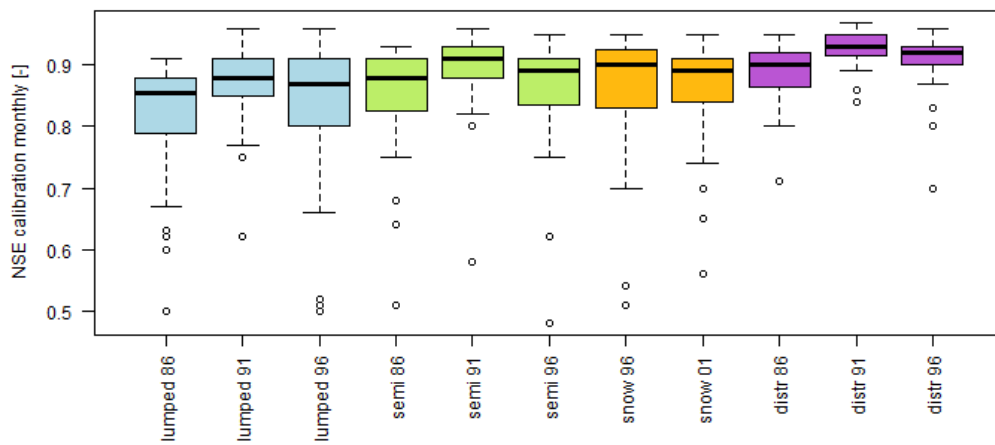
Figure 4.1a shows that for the monthly data all calibration variants achieve a good median between 0.86 and 0.93 for the NSE. While there are some outliers, generally there is not much variability in the NSE values for the calibration variants, since the interquartile ranges are rather small. The calibration period 1991–2000 most of the time leads to the best GOF with values between 0.88 and 0.93. The lumped models overall have a worse performance compared to the other variants, since the medians are below 0.89, and there is more variability in the NSE values. While the snow model has a higher median than the semi-distributed variant, they also have a higher variability in the NSE values. The distributed variants perform the best displaying median values between 0.90 and 0.93, the snow models second best with median values 0.89 and 0.90, with the semi-distributed models a close third showing median values between 0.88 and 0.91. The variant with the best efficiency is distributed 91. The same can be observed for the KGE for the calibration in figure 4.1b, which displays median values between 0.88 and 0.94.

While the logNSE as shown in figure 4.1c generally shows lower medians from 0.75 to 0.87 for all the calibration variants and bigger variability for the individual logNSE values the overall effectiveness is still sufficient. However, different to the NSE and KGE values for the logNSE the calibration period 1996–2005 overall is the period with the best results with values between 0.80 and 0.87. The performance of the lumped and semi-distributed variants is rather similar to each other showing medians from 0.75 to 0.80 and from 0.76 to 0.81 respectively, and the distributed variant has the best results with median values between 0.80 and 0.87. The snow models perform better than the semi-distributed models. The lumped models show the least effectiveness. The variant with the best efficiency is distributed 96.

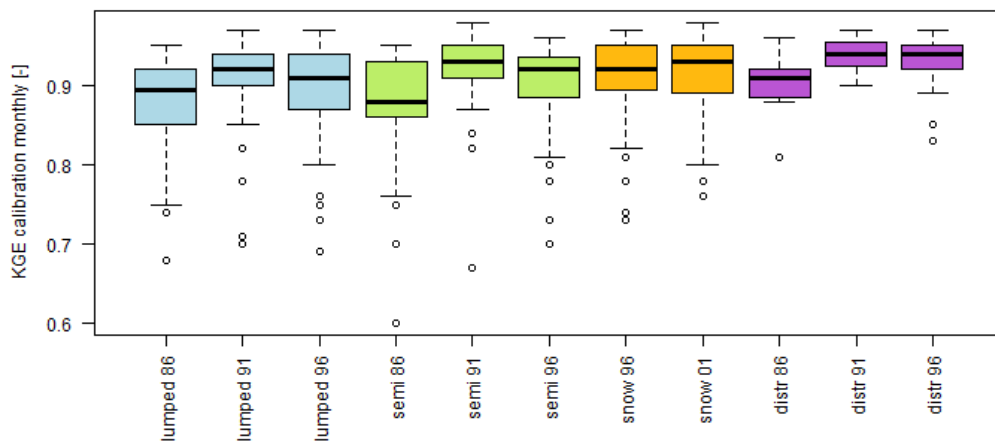
The PBIAS as can be seen in figure 4.1d should be as close to zero as possible. While overall the medians of the variants lead to a good effectiveness displaying medians between -2.85 and 1.00 %, the best fits are for the calibration period 1996–2005 for the variants lumped and distributed and period 1991–2000 for the semi-distributed models as well as 2001–2010 for the snow model. The calibration period 1986–1995 most often leads to the worst fit with median values between -2.85

and -1.00 %. The distributed variants generally result in the best fit for each period displaying medians from -1.00 to 0.50 %. The snow variants have the second best effectiveness with medians ranging from -0.10 to 1.00 %. The lumped models with a median PBIAS of -1.30 to 0.40 % outperform the semi-distributed models with -2.85 to 0.70 %. The variant with the best efficiency is distributed 96.

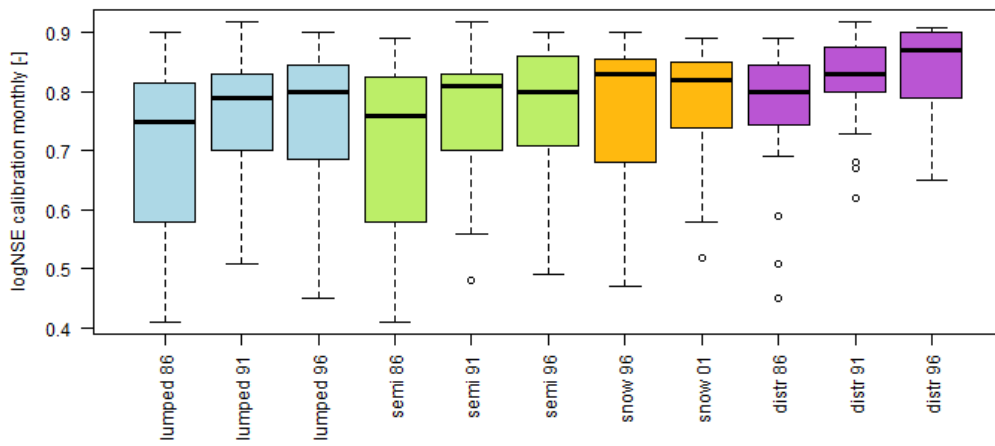
The SCAErr is generally good for the calibration variants its available for as can be seen in figure 4.1e. The median values are between 0.80 and 1.90 %. The best results are for both versions of the snow model, showing medians of 0.80 and 0.89 %. Semi-distributed and distributed variants lead to similar medians with 1.53 and 1.56 % respectively, although the semi-distributed one has less variability in the SCAErrs for the subcatchments. The lumped model leads to the worst results with a median SCAErr of 1.90 %. The variant with the best efficiency is snow 96.



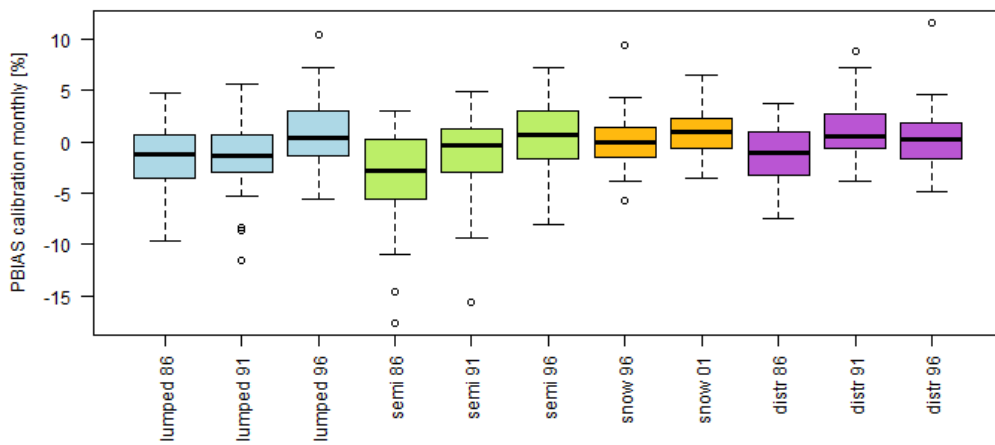
(a) NSE



(b) KGE



(c) logNSE



(d) PBIAS

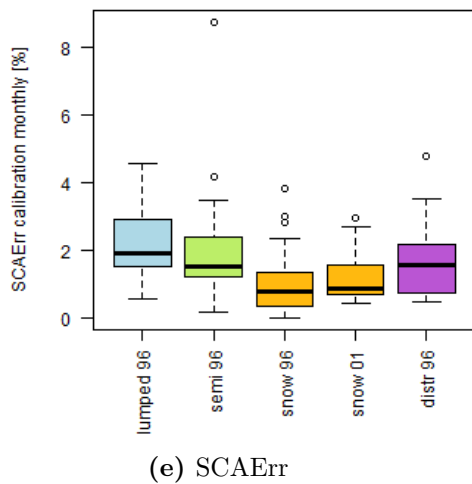


Fig. 4.1: Monthly model efficiencies for different calibration periods and calibration variants in the calibration period. Panels (a)-(d) show different runoff model efficiencies ((a) Nash-Sutcliffe efficiency, (b) Kling-Gupta efficiency, (c) logarithmic Nash-Sutcliffe efficiency, (d) percent bias). Panel (e) shows the snow covered area error. Lumped, semi, snow and distr show different calibration variants for the different calibration periods (see chapter 2.2.1). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for model efficiency for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 19–49.

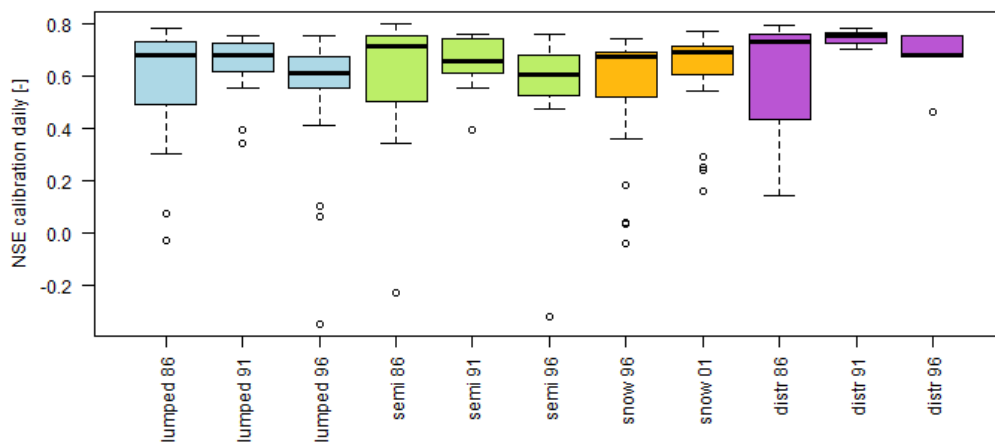
Daily runoff efficiency in calibration period

The efficiency in calibration using daily data is generally worse than with the monthly data as figure 4.2 below shows.

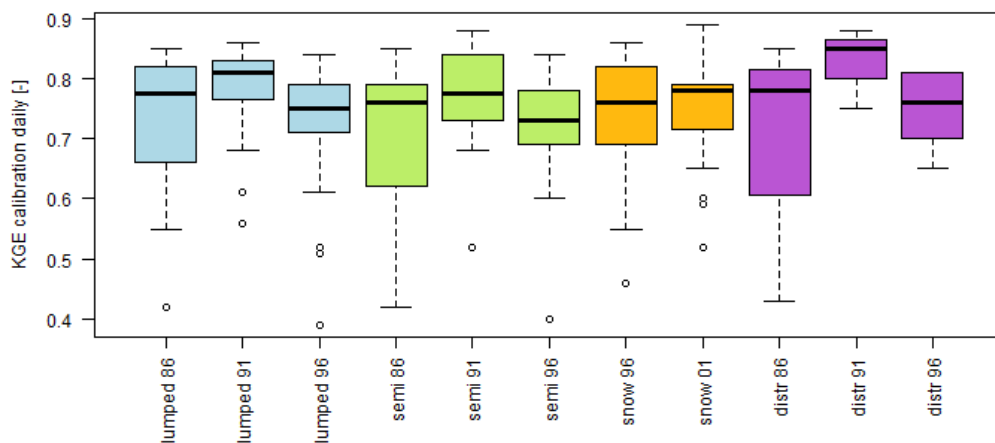
The NSE using daily data can be seen in figure 4.2a. The medians take on values between 0.61 and 0.75. Here the calibration period 1996–2005 can be considered the worst in terms of effectiveness with medians ranging from 0.61 to 0.68. The periods 1991–2000 and 1986–1995 perform similarly to each other in terms of the median with ranges from 0.66 to 0.75 and 0.67 to 0.73 respectively. However, 1991–2000 has less variability for the NSE values for the individual subcatchments. The different models show similar behaviour, but the distributed model has the best effectiveness displaying median values from 0.68 to 0.75, followed by the snow model with 0.67 to 0.69 and the semi-distributed model with 0.61 to 0.71. The variant with the best efficiency is distributed 91. Similar findings can be derived from the KGE, which has a range of medians from 0.73 to 0.85. The main difference is the bigger gap between the variant distributed 91 with a median of 0.85 to the others in a range of 0.73 to 0.81 and the lumped models with the range 0.74 to 0.81 outperforming the semi-distributed models with the range of 0.73 to 0.76 as shown in figure 4.2b.

In figure 4.2c it can be seen that the median of the logNSE for the distributed models with 0.69 to 0.77 indicate a much better effectiveness than for the other variants with 0.53 to 0.61, which all share similar medians for the same calibration periods. Especially variant distributed 96 shows a good performance with a logNSE of 0.77. The snow models have the second best effectiveness with medians from 0.58 to 0.61, followed by the semi-distributed models with medians ranging from 0.56 to 0.61. The variant with the best efficiency is distributed 96.

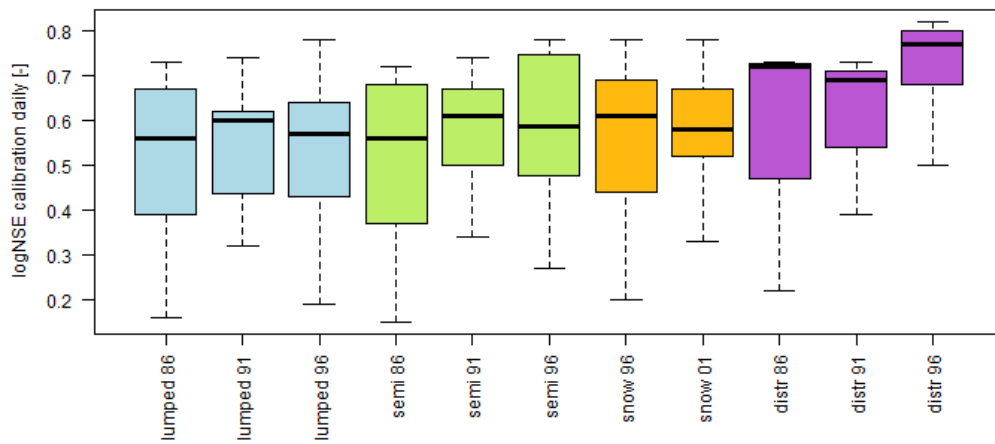
The PBIAS as can be seen in figure 4.2d should be as close to zero as possible. While overall the medians of the variants lead to a good effectiveness ranging from -4.30 to 1.75 %, the best fits are for the calibration period 1996–2005 for the variant lumped and period 1991–2000 for the semi-distributed and distributed models. The snow variants both have the same distance to zero for the medians with -0.8 and 0.8 % which represents the best effectiveness for the SCAErr. The calibration period 1986–1995 generally leads to the worst fit with medians ranging from -2.40 to -4.30 %. The performance of the distributed models with -2.90 to 1.30 % is the second best. The lumped models also perform rather well with a range of -2.40 to 0.00 %, while the semi-distributed models have the worst fits for each period with medians from -4.30 to 1.75 %. The variant with the best efficiency is lumped 96.



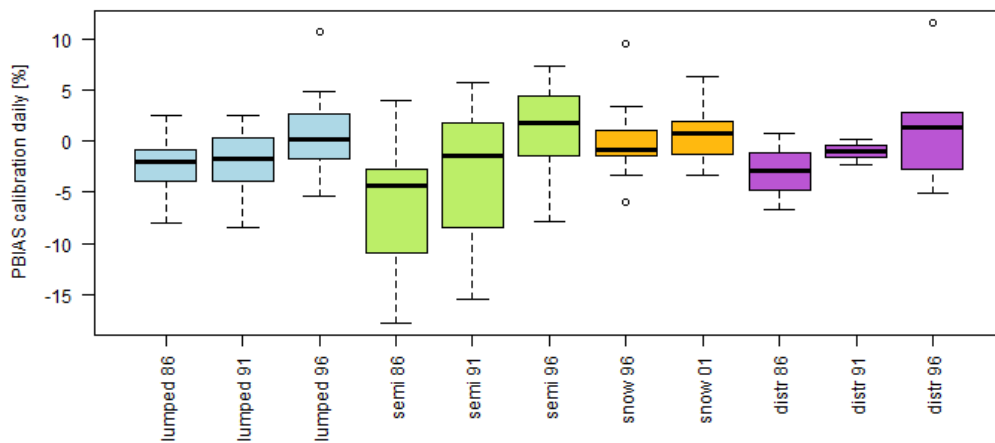
(a) NSE



(b) KGE



(c) logNSE



(d) PBIAS

Fig. 4.2: Daily model efficiencies for different calibration periods and calibration variants in the calibration periods. Panels (a)-(d) show different runoff model efficiencies ((a) Nash-Sutcliffe efficiency, (b) Kling-Gupta efficiency, (c) logarithmic Nash-Sutcliffe efficiency, (d) percent bias). Lumped, semi, snow and distr show different calibration variants for the different calibration periods (see chapter 2.2.1). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for model efficiency for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 3–23.

Comparison of calibration variants

The following section compares distributed 91 and distributed 96 as the two calibration variants with the best effectiveness in the calibration periods. The average for NSE, logNSE and KGE for distributed 96 for monthly data is 0.91, for distributed 91 0.90. For daily data the average of distributed 96 is 0.74, for distributed 91 0.76. So it can be seen that for the calibration the variant distributed 96 has a better effectiveness than distributed 91 for the monthly data for NSE, logNSE and KGE on average. However, for daily data it is the opposite. Since the values

for the monthly data are quite similar to each other, and there are bigger differences between the values for daily data, variant distributed 91 can be considered the better fit for the average NSE, logNSE and KGE. For the PBIAS the best fit for monthly data is for distributed 96 with a median of 0.30 % when distributed 91 has a value of 0.50 %, while the best fit for daily data out of the distributed variants is for distributed 91 with -1.00 %, with distributed 96 having a PBIAS of 1.30 %. However, the differences are once again bigger for the daily data, so distributed 91 can again be considered the better fit. The SCAErr is only available for variant distributed 96 and cannot be used for a comparison. So all in all it can be said that the best fit for the calibration can be achieved with the distributed 91 variant.

4.1.2 Validation model efficiency

Monthly runoff efficiency in validation period

The GOF for the validation via monthly data can be seen in the following figures 4.3. In general, the validation shows a good fit for all the calibration variants.

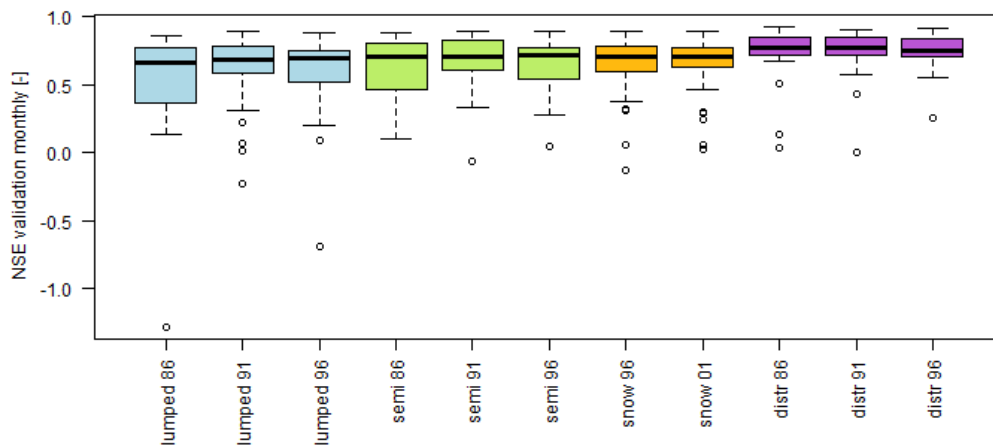
The depiction of the NSE in figure 4.3a implies that all calibration variants lead to a similar performance in the validation period with medians between 0.66 and 0.77. For the lumped and semi-distributed models the calibration period 1996–2005 leads to the best NSE value, while the distributed model has the worst performance in this period according to the median. The snow model has the same median for both periods, but a little bit more variability in NSE values for the individual subcatchments for the aforementioned period. The biggest variability is in the lumped and semi distributed models for period 1986–1995. The distributed model performs the best with median values ranging from 0.75 to 0.77. The semi-distributed model also shows a good effectiveness with 0.71 to 0.72 and performs second best, with the snow model close behind with a median of 0.71 for both calibration periods. The variants with the best efficiencies are distributed 91 and distributed 86.

The KGE has a bigger variability than the NSE and logNSE as shown in figure 4.4b and medians between 0.77 and 0.86. The lumped and distributed models have the best performance in period 1991–2000, while the semi-distributed model performs best in period 1986–1995 and the snow model has the same effectiveness in both periods with a median value of 0.79. Generally, the distributed variants have the best performance, medians ranging from 0.83 to 0.86, with the semi-distributed variants coming in second displaying values from 0.77 to 0.82. The lumped model performed the worst with median KGE values from 0.77 to 0.80. The variant with the best efficiency is distributed 91.

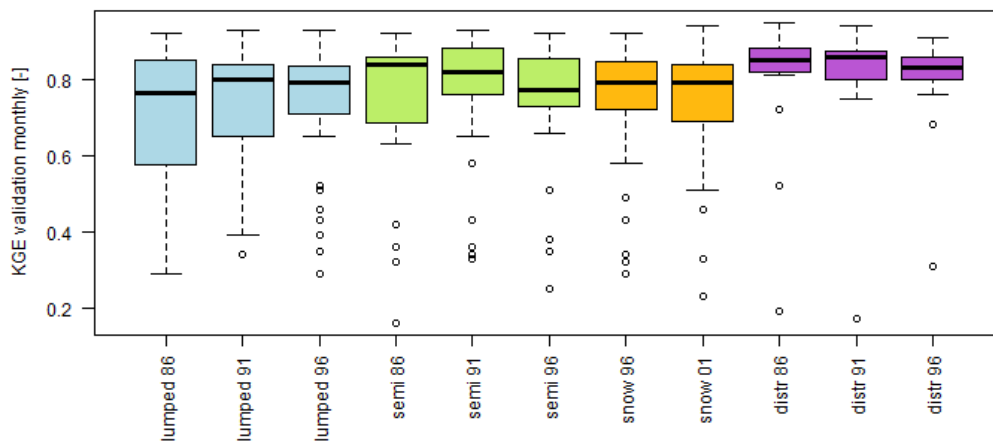
The logNSE also has a small variability in logNSE values for the different subcatchments for all the variants as can be seen in figure 4.3c. The medians range from 0.54 to 0.70. For all of the models besides the lumped model the best performance is in the period 1996–2005. The distributed model once again performs the best, showing medians from 0.61 to 0.70, with the semi-distributed model as second best with a range of 0.55 to 0.59 and the snow model a close third with median logNSEs of 0.54 to 0.59. The variant with the best efficiency is distributed 96.

Figure 4.3d shows that the median PBIAS for the validation lies between -3.40 and 7.70 %. The lumped and semi-distributed models have the best performance for the validation in period 1986–1995. For the snow model period 1996–2005 and for the distributed model period 1991–2000 leads to the best results. There is once again only a small variability for most variants. Generally, the lumped models show the best efficiency with medians ranging from -2.70 to 3.80, the semi-distributed models the second best ranging from -3.40 to 6.30. The distributed models have better fitting medians of 1.20 to 4.40 than the snow models with 6.90 to 7.70. The variant with the best efficiency is semi 86.

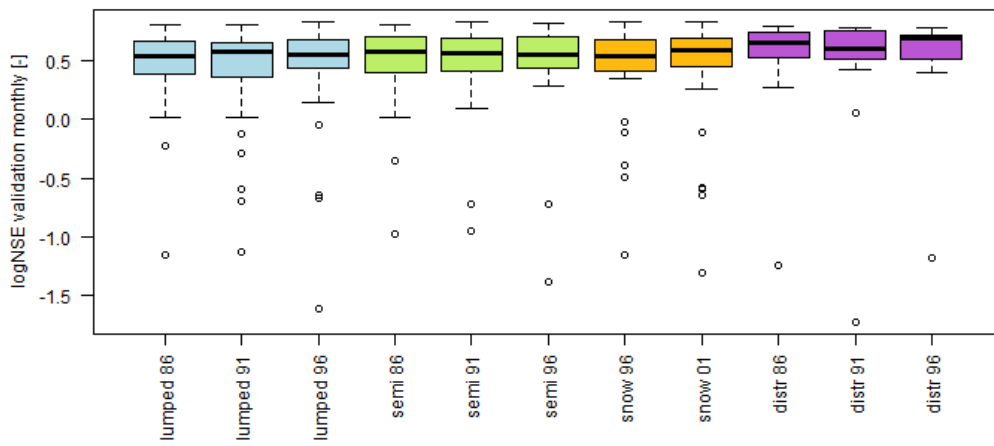
The median SCAErr for the validation ranges from 1.22 to 3.23 %. For all models besides the snow model the best period is 1996–2005 as shown in figure 4.3e. The distributed model once again shows the best effectiveness with medians from 1.22 and 1.39 %, with the value 1.92 % in period 1991–2000 being an outlier. The snow model has the second best performance with 1.52 to 1.76 %, followed by the semi-distributed model with 1.62 to 2.02 %. The lumped model performs noticeably poorer with a range of 2.41 to 3.23 %. The variant with the best efficiency is distributed 96.



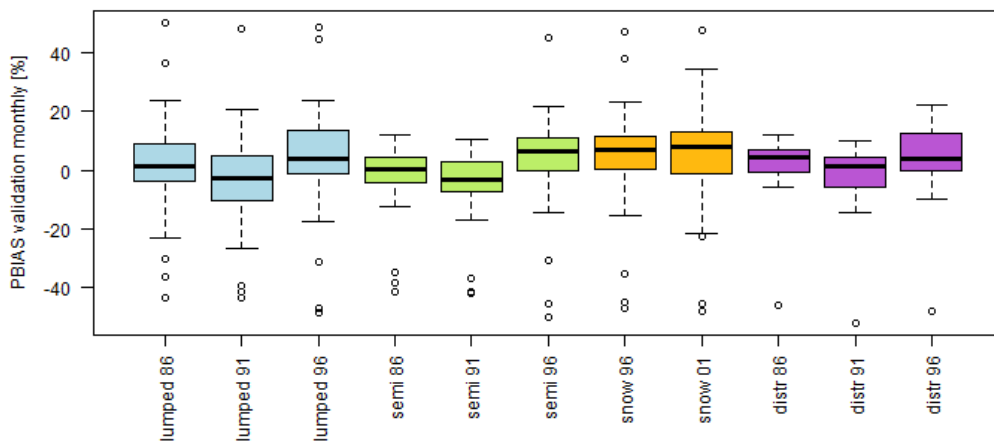
(a) NSE



(b) KGE



(c) logNSE



(d) PBIAS

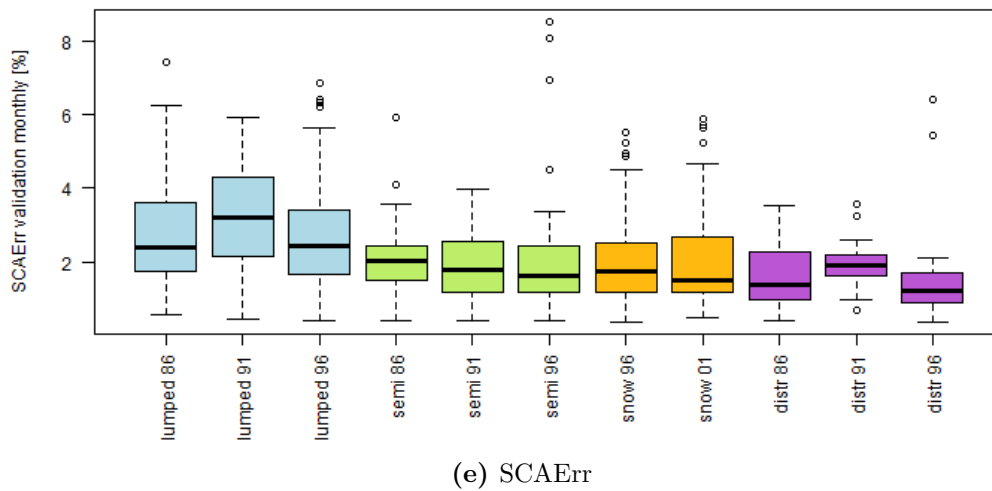


Fig. 4.3: Monthly model efficiencies for different calibration periods and calibration variants in the validation period. Panels (a)-(d) show different runoff model efficiencies ((a) Nash-Sutcliffe efficiency, (b) Kling-Gupta efficiency, (c) logarithmic Nash-Sutcliffe efficiency, (d) percent bias). Panel (e) shows the snow covered area error. Lumped, semi, snow and distr show different calibration variants for the different calibration periods (see chapter 2.2.1). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for model efficiency for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 19–49.

Daily runoff efficiency in validation period

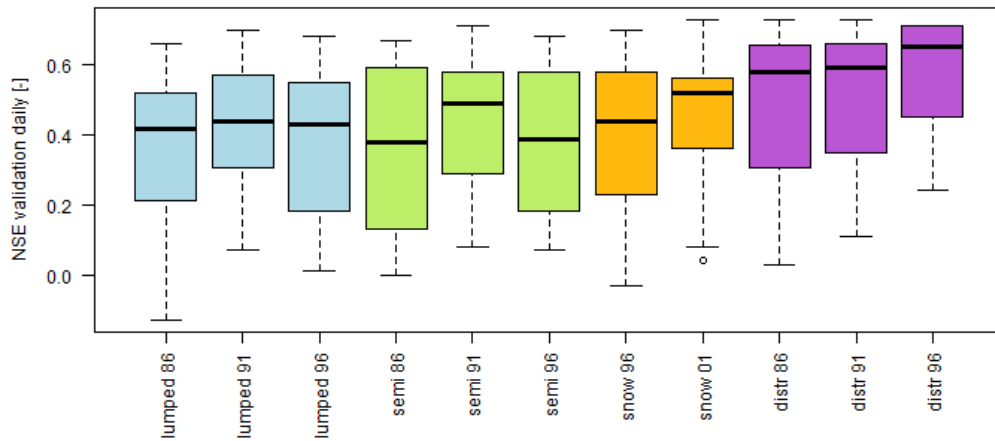
Figure 4.4 shows that GOF values for the validation via daily data generally have a bigger variability than with the monthly discharge data.

The NSE can be seen in figure 4.4a and the medians have a range from 0.38 to 0.65. The best median and the smallest variability are depicted for the lumped and semi-distributed models in period 1991–2000, the snow model in period 2001–2010 and for the distributed model in period 1996–2005. Generally, the distributed model performs the best in terms of median NSE with values from 0.58 to 0.65. This is followed by the snow model with a range of 0.44 to 0.52 and then the lumped model with median values from 0.41 to 0.43. The variant with the best efficiency is distributed 96.

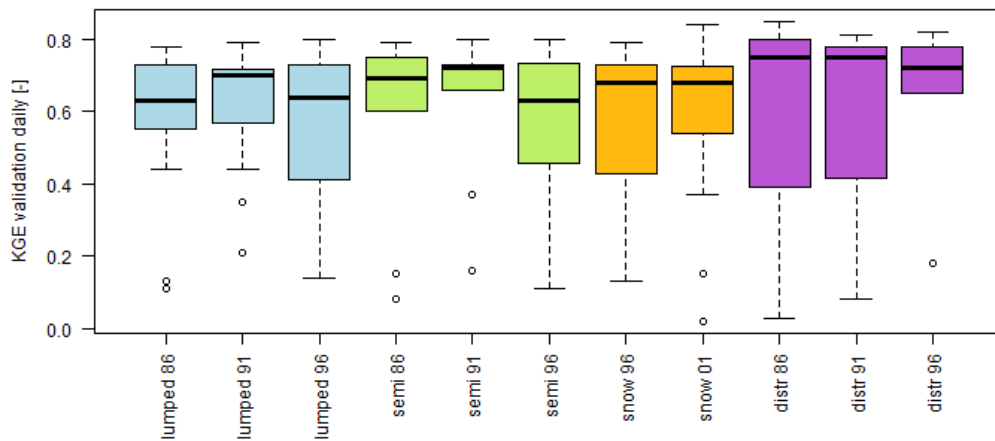
The logNSE as shown in figure 4.4c performs similarly as the NSE with a range of 0.33 to 0.59 for the medians. However, the semi-distributed models with values from 0.33 to 0.44 have better effectiveness than the lumped models with 0.33 to 0.40. The variant with the best efficiency is distributed 96.

The KGE can be seen in figure 4.4b. The medians range from 0.63 to 0.75. The best median and the smallest variability in values for the individual KGEs are depicted in the lumped and semi-distributed models in the period 1991–2000 and the snow model in period 2001–2010. The distributed model has the highest median in period 1991–2000 and period 1986–1995 and the lowest variability in period 1996–2005. The distributed models perform the best with median values from 0.72 to 0.75, the effectiveness of the semi-distributed and snow models the second best with medians ranging from 0.63 to 0.72 and medians of 0.68 respectively. The variants with the best efficiencies are distributed 91 and distributed 86.

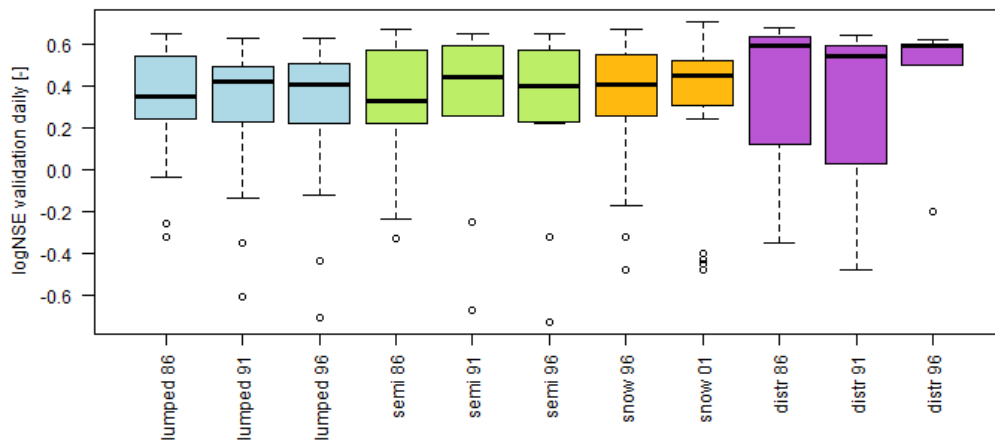
The PBIAS is shown in figure 4.4d. The medians range from -0.80 to 16.10 %. The period with the smallest PBIAS varies for the different models. It is period 1991–2000 for the lumped and distributed, period 1986–1995 for the semi-distributed and period 1996–2005 for the snow model. The lumped models perform the best with medians ranging from -0.55 to 3.70 %. The semi-distributed models have the second best medians ranging from -0.8 to 9.20 %, followed by the snow models with 6.70 to 8.10 %. The variant with the best efficiency is lumped 91.



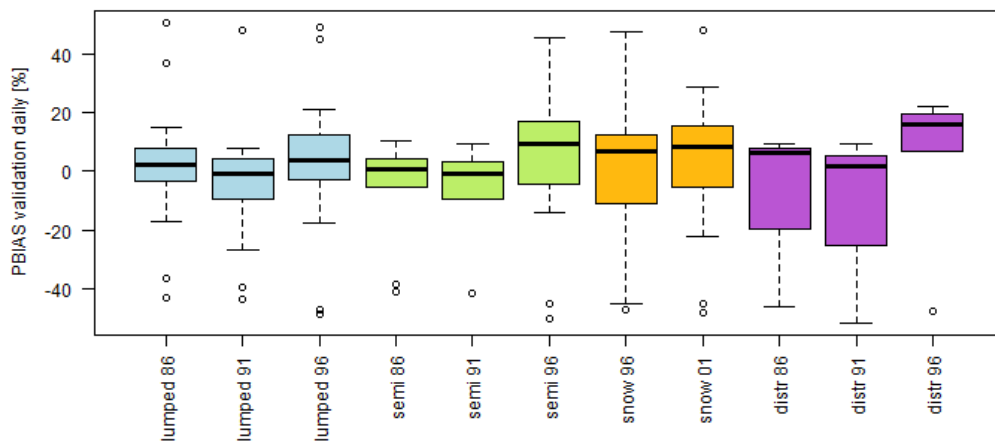
(a) NSE



(b) KGE



(c) logNSE



(d) PBIAS

Fig. 4.4: Daily model efficiencies for different calibration periods and calibration variants in the validation period. Panels (a)-(d) show different runoff model efficiencies ((a) Nash-Sutcliffe efficiency, (b) Kling-Gupta efficiency, (c) logarithmic Nash-Sutcliffe efficiency, (d) percent bias). Lumped, semi, snow and distr show different calibration variants for the different calibration periods (see chapter 2.2.1). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for model efficiency for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 3–23.

Comparison of calibration variants

In the following section the distributed calibration variants are compared because they are the variants with the best effectiveness in the validation period. The average of the medians for NSE, logNSE and KGE for distributed 96 for monthly data is 0.96, for distributed 91 0.75 and for distributed 86 0.76. For daily data the average of distributed 96 is 0.65, for distributed 91 0.63 and for distributed 86 0.64. When comparing the three variants to each other it can be seen that distributed 96 has the best fit on average for both daily and monthly data when evaluating with

NSE, logNSE and KGE, followed by distributed 86. However, the differences between the three calibration variants are slim.

When looking at the evaluation in percent via PBIAS the variant distributed 91 performs best out of the three distributed variants with a median of 1.20 %, compared to 4.10 % for distributed 96 and 4.40 % for distributed 86. The SCAErr shows the best median efficiency for distributed 96 with 1.22 %, second best for distributed 86 with 1.39 % and third for distributed 91 with 1.92 %. The PBIAS with daily data leads to the best performing variant being distributed 91 with a median of 1.50 %, followed by distributed 86 with 6.20 % and the outlier of distributed 96 with 16.10 %. So it can be seen that while distributed 91 has the best efficiency for the PBIAS, it also leads to the worst fit for the SCAErr. Distributed 96 performs best for the SCAErr out of the distributed variants, however it is only second best for PBIAS with monthly data and third for PBIAS with daily data. Given the distributions of the different PBIAS and SCAErr values the variant distributed 91 leads to the best performance out of the distributed variants. Due to the bad median fit for the PBIAS with daily data the distributed 96 variant only performs third best in terms of PBIAS and SCAErr. This results in distributed 91 being the calibration variant which leads to the best fit.

4.1.3 Spatial variability of model efficiency

In the following paragraphs a comparison between the calibration and validation for the daily and monthly data will be made for calibration variant semi-distributed 96. The variant was chosen as a representative for the average behaviour of the subcatchments.

To compare the behaviour for the NSE, figure 4.5 is used. Figure 4.5a shows the distribution of the NSE for the calibration with monthly data for the whole catchment. Generally, a good performance can be seen, with most of the values being between 0.80 and 1.00. The two subcatchments with the worst performances are located in the southern part of the catchment belonging to Austria, with values between 0.40 and 0.60 and 0.60 and 0.70 respectively.

For the validation using monthly data shown in figure 4.5b the GOF is more variable. Most of the subcatchments with a bad effectiveness of less than 0.40 are located in the southern part of the catchment belonging to Austria, while one of the subcatchments is up in the north and another one is in the west. Many of the subcatchments with a poorer fit for the calibration also now have a poorer fit for the validation, however not all of them. The Austrian part of the catchment seems to perform poorer on average than the Czech part.

For the calibration using daily data seen in figure 4.5c there are spatial patterns recognizable. The northern subcatchments tend to have a better fit with values between 0.60 and 0.70 than the subcatchments in the middle regions, with values mostly between 0.40 and 0.60 and sometimes values smaller than 0.40. In the eastern Austrian part of the Thaya basin the subcatchments have a poor GOF of under 0.60, while the western part has a good effectiveness of over 0.60. In the north of the Austrian part there are two subcatchments with a very good effectiveness of over 0.70.

The validation with daily data is shown in figure 4.5d and displays spatial patterns. Like in the calibration the northern subcatchments with values from 0.40 to 0.60 show a better fit than the middle parts of the catchment, displaying many values under 0.40. The Austrian parts are generally represented with a poor GOF with many values of under 0.4, however the only two subcatchments with a good GOF are the two subcatchments located in the northern regions of the Austrian part, having a NSE of between 0.60 and 0.70. Once again many of the subcatchments with a poorer fit for the calibration also now have a poorer fit for the validation.

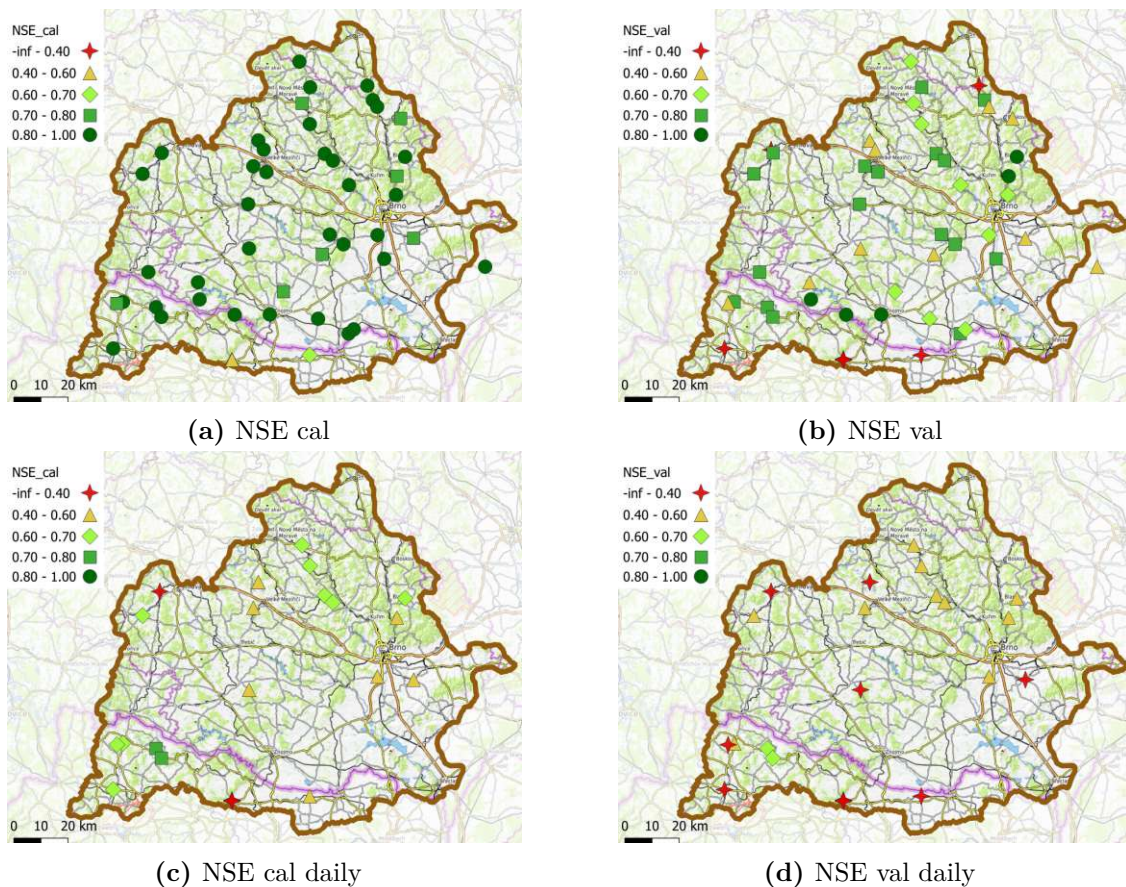


Fig. 4.5: Nash-Sutcliffe efficiency for semi-distributed calibration in period 1996-2005. Panel (a) shows the monthly runoff efficiency in the calibration period, (b) shows the monthly runoff efficiency in the validation period, (c) shows the daily runoff efficiency in the calibration period, (d) shows the daily runoff efficiency in the validation period.

In figure 4.6 the GOF of the KGE is compared.

Figure 4.6a shows a generally very good effectiveness for the calibration with monthly data with most values being between 0.80 and 1.00. Only a few subcatchments in the east, south and west have a little bit poorer performances of below 0.80.

The validation with monthly data in figure 4.6b shows once again that not all subcatchments with poorer performance in the calibration necessarily have a bad performance in the validation, but many do. The Austrian part of the catchment seems to have generally a worse GOF than the Czech part, having less values over 0.80 and more under 0.60 compared to the amount of catchments.

In figure 4.6c the performance for the calibration with daily data is shown. There are no spatial patterns observable. The overall performance is quite well displaying many values over 0.70, with only one catchment performing poor with a value of under 0.40.

Figure 4.6d shows the poorer performance in the Austrian part of the catchment for the validation using daily data, with most showing values under 0.60. However, once again the two subcatchments in the northern part of Austria perform well with values between 0.70 and 0.80. While for many subcatchments a poorer performance in the calibration means a poorer performance in the validation as well, for some catchments this is not the case.

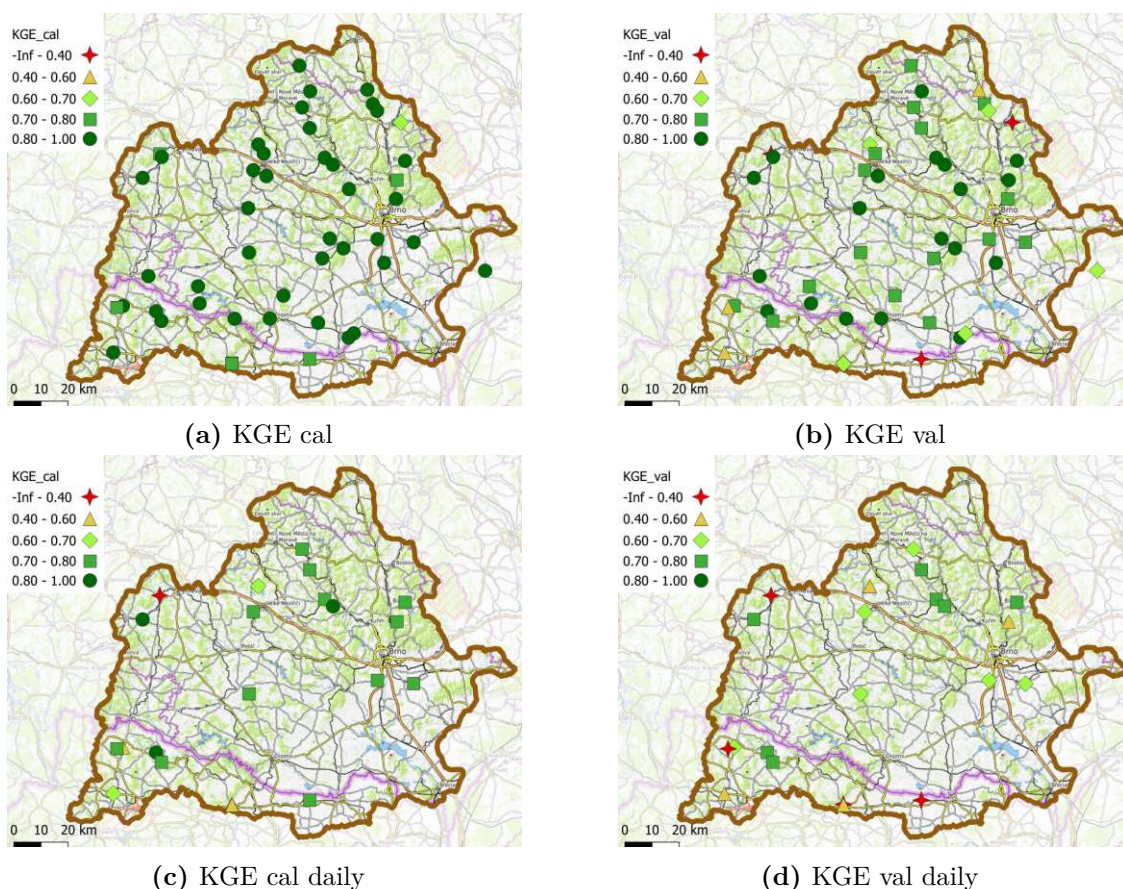


Fig. 4.6: Kling-Gupta efficiency for semi-distributed calibration in period 1996-2005. Panel (a) shows the monthly runoff efficiency in the calibration period, (b) shows the monthly runoff efficiency in the validation period, (c) shows the daily runoff efficiency in the calibration period, (d) shows the daily runoff efficiency in the validation period.

Figure 4.7 shows the differences between the logNSE for calibration and validation with daily and monthly data.

The logNSE for calibration via monthly data displays a spatial pattern in terms of the western subcatchments with many values over 0.80 generally performing better than the eastern subcatchments with many values between 0.60 and 0.80 as can be seen in figure 4.7a. The performance for the Austrian subcatchments seems to be of the same level as for the Czech subcatchments.

The validation with monthly data has no spatial patterns as shown in figure 4.7b. Once again, a better performance in the calibration does not necessarily lead to a good performance in the validation, but it often does.

In the calibration using daily data the western part of the Austrian section and the northern part of the catchment have a very good performance as can be seen in figure 4.7c, displaying many values of over 0.70 and 0.60 respectively. The efficiency for the validation with daily data in figure 4.7d can generally be considered poor because of its many subcatchments with values under 0.40 aside from the northern parts of the catchment and the northern section of the Austrian part of the catchment where many values are above 0.40.

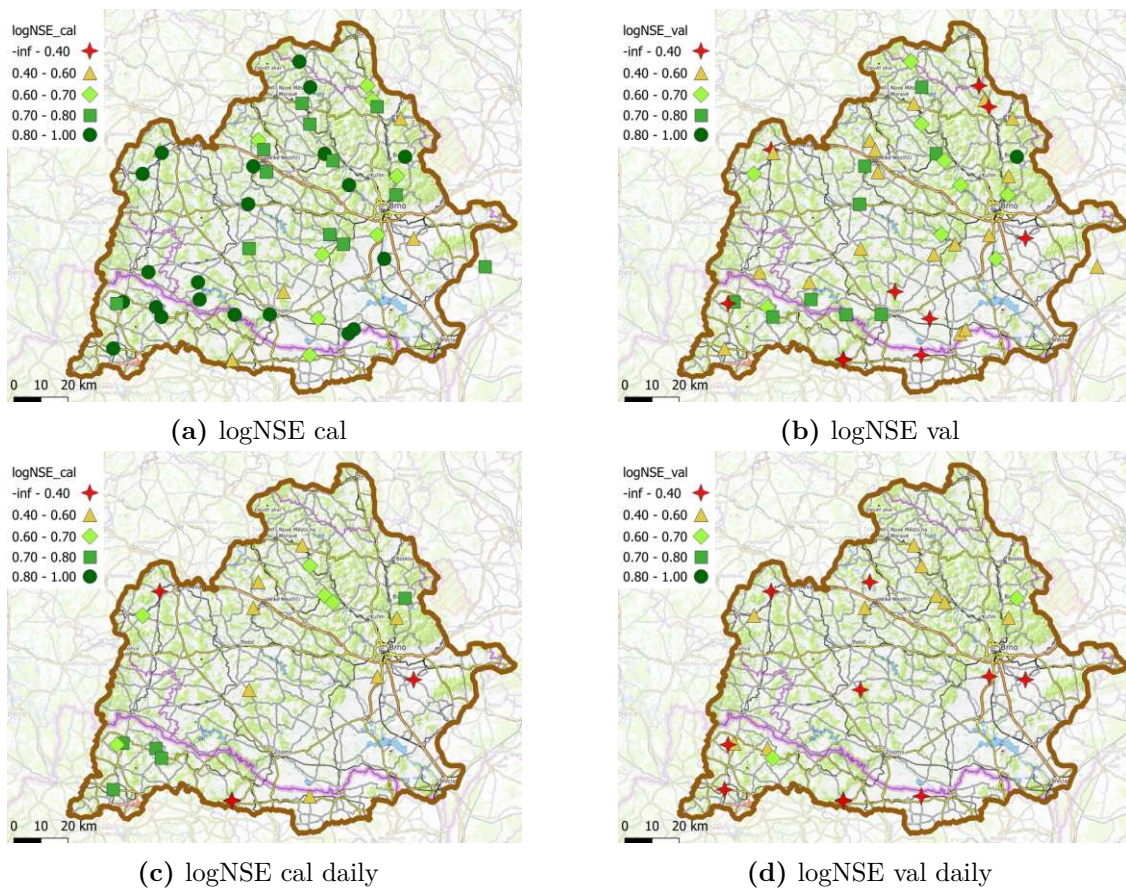


Fig. 4.7: Logarithmic Nash-Sutcliffe efficiency for semi-distributed calibration in period 1996-2005. Panel (a) shows the monthly runoff efficiency in the calibration period, (b) shows the monthly runoff efficiency in the validation period, (c) shows the daily runoff efficiency in the calibration period, (d) shows the daily runoff efficiency in the validation period.

Figure 4.8 shows the performance of the PBIAS.

In figure 4.8a it can be seen that the northern parts with more subcatchments with values under 2 % perform generally better than the middle and southern parts for the calibration via monthly data. In the validation, however, as seen in figure 4.8b the performance throughout the Czech part of the catchment seems to not have any spatial patterns, while the Austrian parts now perform poorly with many values with an absolute amount of over 18.00 %.

For the calibration via daily data figure 4.8c shows a poorer performance in the middle section of the catchment with some values over 6.00 % compared to the northern and southern regions with values under 6.00 %, while the validation in figure 4.8d once again has a poor effectiveness for the Austrian parts, showing many subcatchments with values over 18.00 %.

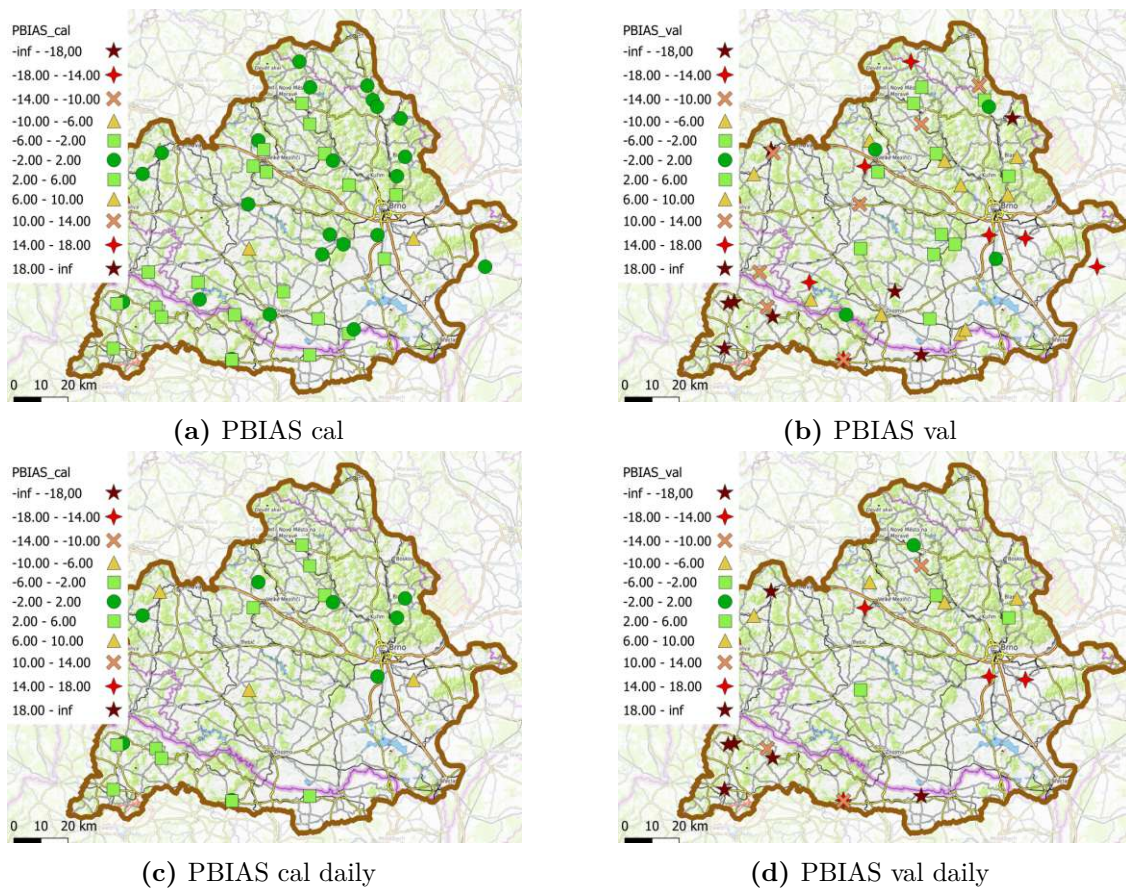


Fig. 4.8: Percent bias for semi-distributed calibration in period 1996-2005. Panel (a) shows the monthly runoff efficiency in the calibration period, (b) shows the monthly runoff efficiency in the validation period, (c) shows the daily runoff efficiency in the calibration period, (d) shows the daily runoff efficiency in the validation period.

The effectiveness of the SCAErr is shown in figure 4.9. While generally a good performance is achieved for the calibration period with most values smaller than 6.00 % as can be seen in figure 4.9a the northern parts of the catchment perform a little bit poorer than the rest. The same can be said for the validation in figure 4.9b.

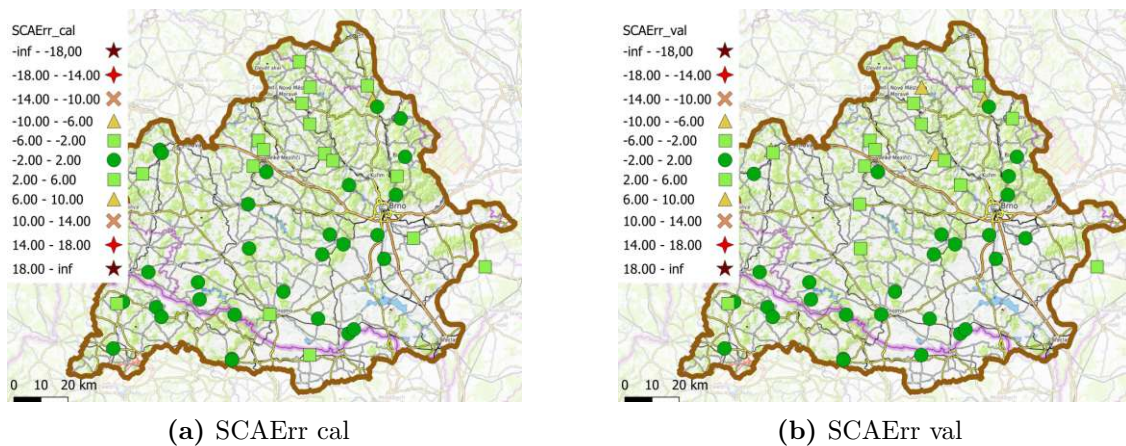


Fig. 4.9: Snow covered area error for semi-distributed calibration in period 1996-2005. Panel (a) shows the monthly runoff efficiency in the calibration period, (b) shows the monthly runoff efficiency in the validation period.

Generally it can now be said that while a good performance in the calibration does not guarantee a good GOF in the validation, it most often does lead to it. In terms of spatial patterns for the calibration with monthly and daily data there are no shared patterns for the different values. As for the validation with monthly data, the Austrian subcatchments are more likely to show a bad efficiency for all the values aside from the SCAErr, which has the worst values for the northern subcatchments. This can be due to the fact that for Austria naturalized data is only available for two catchments. The same can be said for the validation via daily data. It is notable that there seem to be no spatial patterns due to the changes in height throughout the catchment, with the south-east being the lowest part.

4.1.4 Variability of model parameters

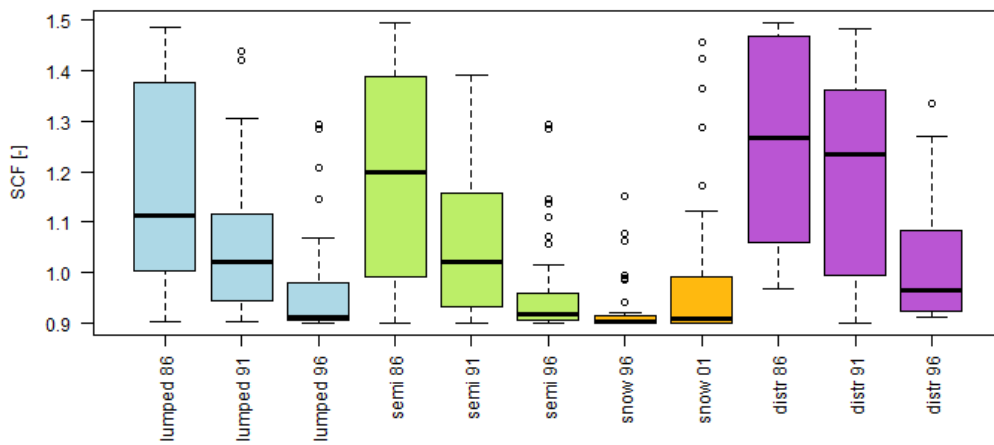
The distribution of the various parameters are vastly different, as can be seen in figure 4.10. For the SCF the medians and variability of the value generally tend to be higher the further away the period is from the validation period, except for the snow variants. The median tends to be in the lower half of the parameter range aside from the distributed model. Period 1986–1995 shows the biggest variability of the parameter, 1996–2005 the least variability. The different periods lead to differences in the medians of about 0.1. For the semi-distributed model, the difference between semi 91 and semi 96 is about the same, however the difference from semi 91 to semi 96 is approximately 0.2. The medians of the snow model are about the same with a value of approximately 0.9. The difference between distributed 86 and distributed 91 is rather small with about 0.05, the difference from distributed 91 to distributed 96 however is about 0.25.

For the T_S the variability is more similar for the different calibration variants aside from the distributed model compared to the SCF. However, the median is very different most of the time. For the lumped models lumped 96 has a very different median to the other periods with a gap of more than 1 °C between them. The medians for the semi-distributed models are within less than 0.5 °C of each other. The snow models differ by about 1 °C, with snow 96 tending towards higher values compared to snow 01. Distributed 91 and distributed 96 have similar medians to each other, however distributed 86 is approximately 2 °C above them.

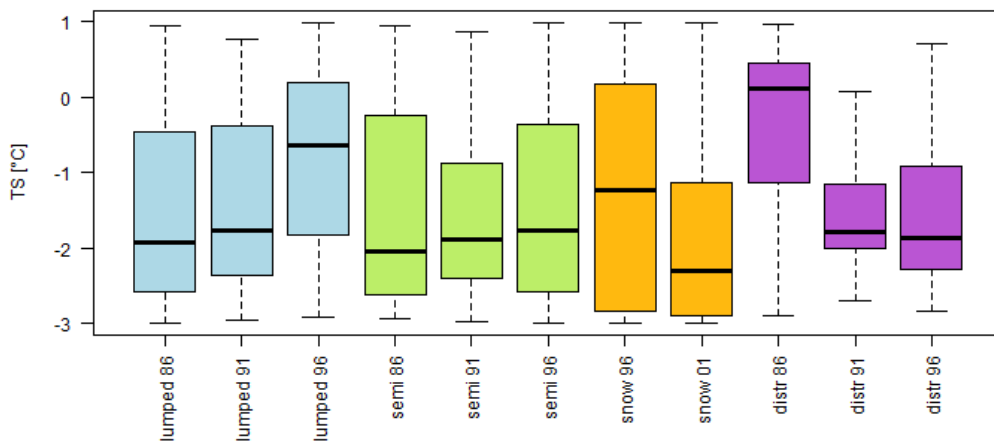
For β the lumped and semi-distributed models and the snow 96 variant lead to very similar boxplots and medians of approximately 4. The snow 01 variant has a a little bit higher median of around 5, as does the distributed 96 model, which however has a bigger variability of values.

Distributed 86 and distributed 91 lead to median values of about 6 with bigger variability than the other models.

The medians of k_2 are very different for the various calibration variants, as is the variability of the values over the catchment. The medians and variability for the lumped and semi-distributed models are similar for each period, with calibration period 1996–2005 leading to the smallest medians of around 160 days and the biggest variability throughout the catchment, and 1991–2000 being responsible for the highest median of about 230 days and the smallest variability. Snow 96 also leads to similar results as lumped 96 and semi-distributed 96. Snow 01 results in a higher median of approximately 220 and a higher variability. Distributed 86 and distributed 91 both lead to values around 190 days, however distributed 91 has a bigger variability. Distributed 96 shows the lowest median for k_2 of around 130 days.



(a) SCF

(b) T_S

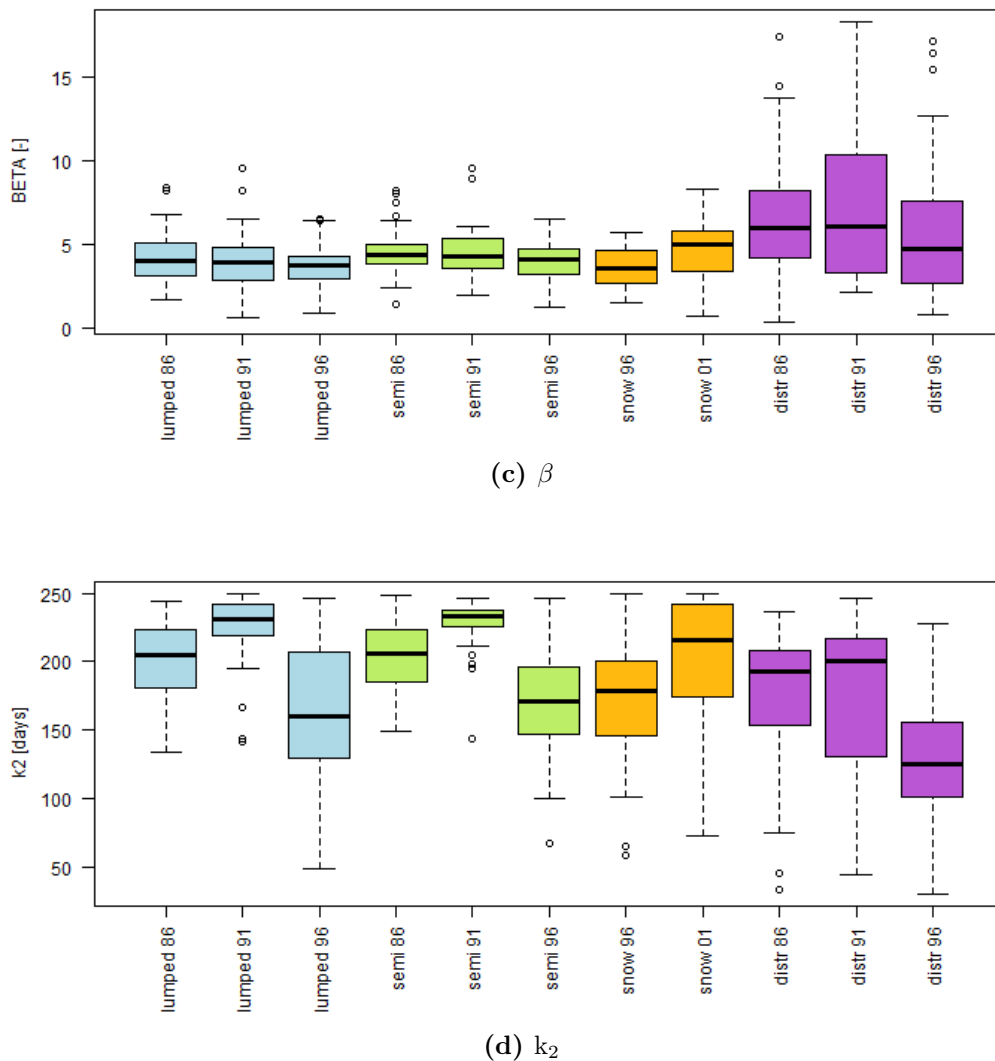
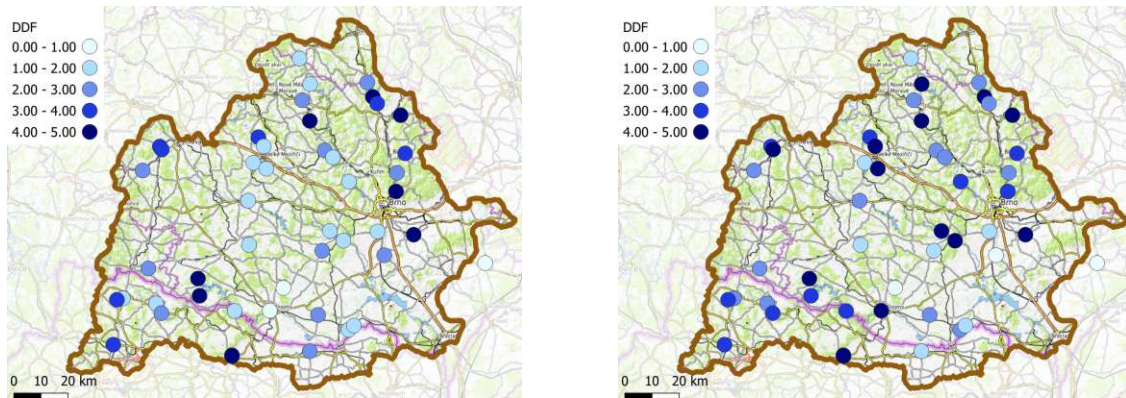


Fig. 4.10: Model parameters for different calibration periods and calibration variants. Panel (a) shows the snow correction factor, (b) threshold temperature below which precipitation is snow, (c) the non-linear parameter for runoff production and (d) storage coefficient for slow response. Lumped, semi, snow and distr show different calibration variants for the different calibration periods (see chapter 2.2.1). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for model parameters for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 19–49.

All in all, it can be said that the lumped, semi-distributed and snow model often times lead to the same behaviour for the same time periods, while the distributed model usually is different.

In the following sections a comparison between a few selected model parameters is made for the semi-distributed and distributed models for period 1996–2005. However, it has to be noted that the headcatchments of the distributed models share the same parameters as the semi-distributed models because of the calibration process.

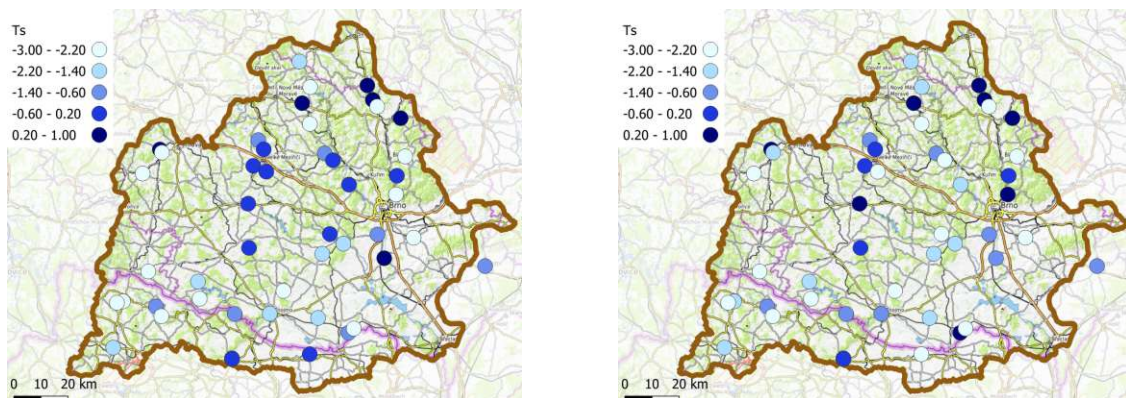
In figure 4.11 the different values for the DDF can be seen. The subcatchments generally take on higher values for the distributed model than for the semi-distributed model, with many showing values above 3 mm/°C/day. While for the semi-distributed model most of the time only the subcatchments on the fringes of the catchment have higher parameters, for the distributed model mostly the lower regions in the south-east have lower parameter values below 2 mm/°C/day.



(a) Semi-distributed calibration in period 1996-2005 (b) Distributed calibration in period 1996-2005

Fig. 4.11: Comparison of degree day factor [mm/°C/day]. Panel (a) shows the semi-distributed values in the calibration period 1996-2005, (b) shows the distributed values in the calibration period 1996-2005.

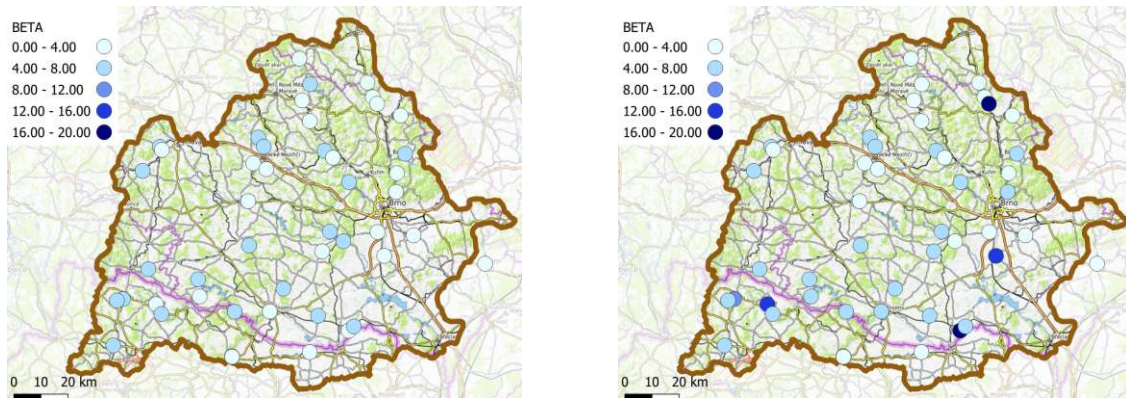
In figure 4.12 the different values for the T_S can be seen. The southern and northern subcatchments generally take on similar values for the semi-distributed and distributed models. The middle regions tend to have more parameters with similar values in the semi-distributed variant. The distributed variant has more variability in the middle regions.



(a) Semi-distributed calibration in period 1996-2005 (b) Distributed calibration in period 1996-2005

Fig. 4.12: Comparison of threshold temperature below which precipitation is snow [°C]. Panel (a) shows the semi-distributed values in the calibration period 1996-2005, (b) shows the distributed values in the calibration period 1996-2005.

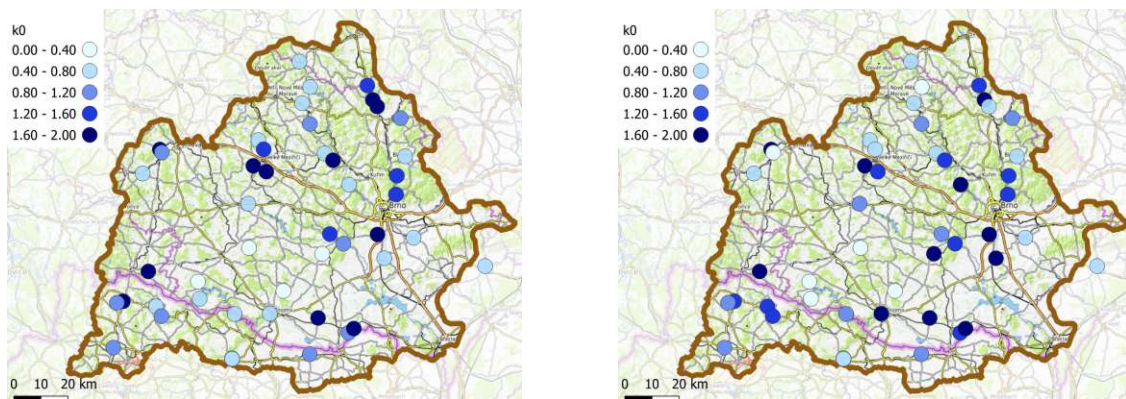
For β figure 4.13 shows more variability for the distributed calibration than for the semi-distributed calibration. While for the semi-distributed model there are mostly small values lower than 8.00, especially in the north and east, the distributed model also shows higher values over 12.00 in the east and south.



(a) Semi-distributed calibration in period 1996-2005 (b) Distributed calibration in period 1996-2005

Fig. 4.13: Comparison of non-linear parameter for runoff production [-]. Panel (a) shows the semi-distributed values in the calibration period 1996-2005, (b) shows the distributed values in the calibration period 1996-2005.

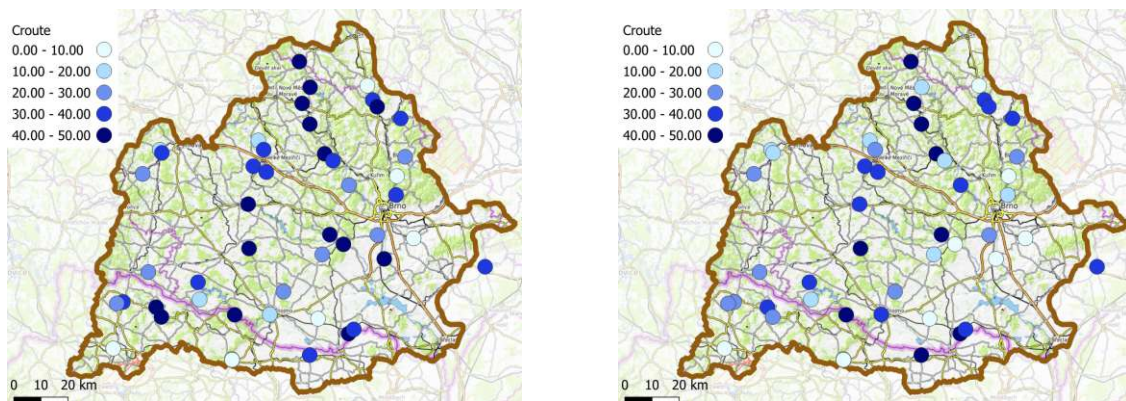
Figure 4.14 shows a high variability for k_0 for the semi-distributed model without spatial patterns. While the distributed parameters change in values, there is still a high variability without spatial patterns.



(a) Semi-distributed calibration in period 1996-2005 (b) Distributed calibration in period 1996-2005

Fig. 4.14: Comparison of storage coefficient for very fast response [day]. Panel (a) shows the semi-distributed values in the calibration period 1996-2005, (b) shows the distributed values in the calibration period 1996-2005.

As shown in figure 4.15 in the northern part of the catchment the parameter C_{ROUTE} shows high values for the semi-distributed model, with many being over 40 days²/mm, while showing a great variability for the whole catchment. The distributed model also shows a big variability, however there are no spatial patterns obtainable.



(a) Semi-distributed calibration in period 1996-2005 (b) Distributed calibration in period 1996-2005

Fig. 4.15: Comparison of free scaling parameter [day^2/mm]. Panel (a) shows the semi-distributed values in the calibration period 1996-2005, (b) shows the distributed values in the calibration period 1996-2005.

There is no universal distribution or spatial pattern for all the parameter values, not even for the differences in altitude. Even the same parameter can take on widely different values for two different calibration variants.

4.2 Hydrological projections

In the following paragraphs the hydrological projections for distributed 91, the calibration variant with the best effectiveness, are discussed.

4.2.1 Comparison of seasonal data

Figure 4.16 below shows the seasonal changes in discharge for different climate projections compared to a historical 30-year period with the parameters from the calibration variants distributed 91 for SSP 126. As can be seen there are several months where no consensus can be reached if the discharge will increase or decrease. Also, the different climate projections show different patterns for the year, so there is no climate projection at the top or the bottom for the whole year. For January all climate models indicate an increase in discharge, varying between 6 % for the GFDL and 31 % for CMCC. February will also lead to increases with values between 3 % for GFDL and 16 % for MRI. March is the first month without certainty if increases or decreases will happen, showing values between -11 % for EC and 23 % for TAI. April and May will see decreases in discharges, varying from -32 to -0.2 % for April and -25 to -3 % for May. It is uncertain whether the discharge will increase or decrease during the other months of the year. June shows values between -33 % for CMCC, which is the highest decrease of the year, and 3 % for MPI. For July to November the highest increase in discharge is projected by the MRI with values from 39 % in July to 20 % in November, with the highest increase of the year being in July. The highest increase in December is established by the CMCC with 10 %. The CMCC also indicates the highest decrease in discharge for July and August with -15 and -20 % respectively. For September to December the EC shows the highest decrease with values from -20 to -10 %. The smallest difference between highest increase or lowest decrease and highest decrease is in February with 13 %, the biggest difference in August with 57 %.

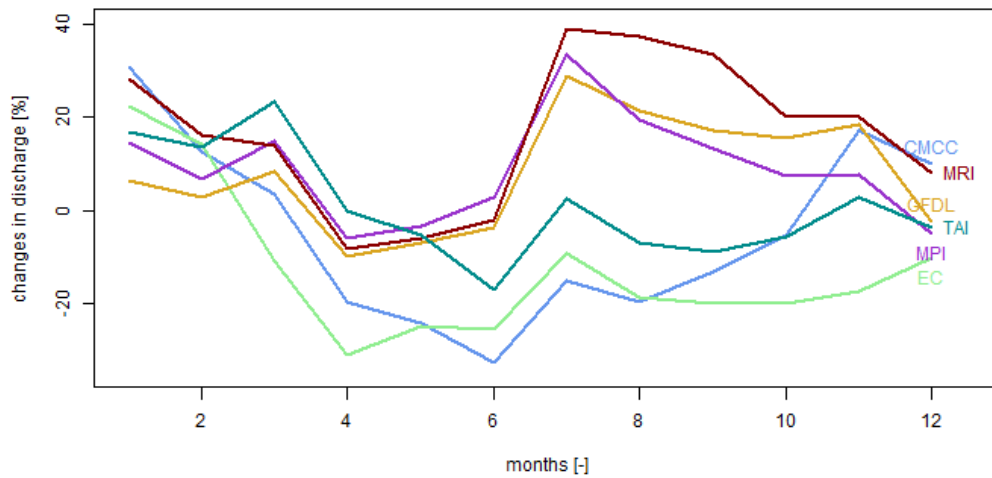


Fig. 4.16: Projections of seasonal runoff changes estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1991-2000 and a 30-year historical period for reference.

For SSP 245 as shown in figure 4.17 the only projection indicating an increase in discharge is climate model CMCC for January to March and for November. The other projections show decreases and are closer to each other in terms of values. For January to March the increase indicated by CMCC is between 25 and 16 %, with January showing the highest increase, and the highest decrease shown by TAI is between -85 and -83 %. The lowest decrease projected by EC is between -60 and -53 %. In April and May, the highest decrease stems from the MRI model with values of -86 %. From June onwards the TAI model is again responsible for the highest decreases, showing values between -87 and -83 % with the highest decrease being in June. The CMCC displays values from -29 to -3 % indicating a decrease in discharge for April to October, with the highest decrease being in June. November shows an increase in discharge by 5 %, December once more a decrease with -1 %. The EC displays the second lowest decreases for April to July with values between -68 and -59 %. For the rest of the year GFDL is responsible for the second lowest decreases from -62 to -54 %. The biggest difference between highest increase or lowest decrease and highest decrease is in January with 108 %, the smallest difference in June with 57 %.

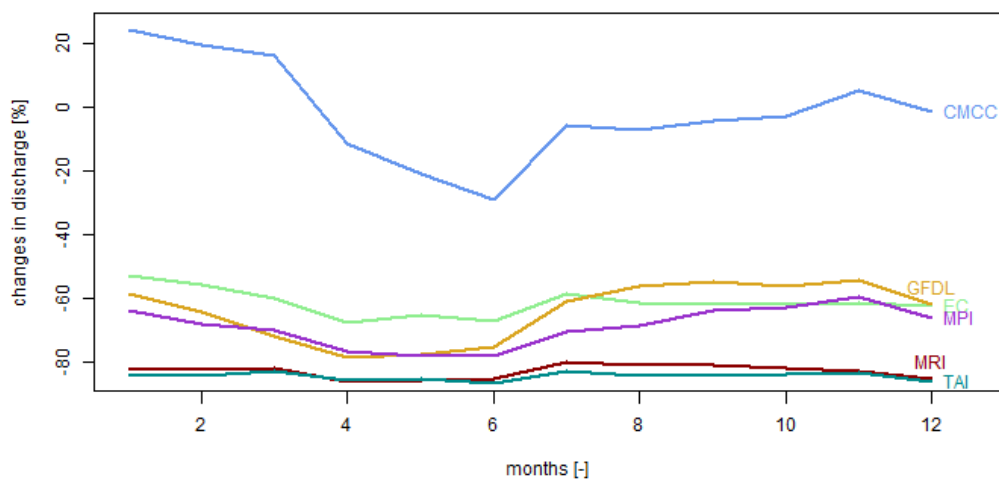


Fig. 4.17: Projections of seasonal runoff changes estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1991-2000 and a 30-year historical period for reference.

For SSP 370, as can be seen in figure 4.18, all six climate models predict a decrease in discharge for the whole year. The CMCC model projects the least change in discharge, with values between -44 % in June and -9 % in January. The highest decrease can be seen for the TAI model, displaying values between -89 % in June and -79 % in January. Generally, it can be said that the climate models follow more similar patterns for this pathway, with all of them showing their highest decrease somewhere between April and June and most having the smallest decrease in January. The largest differences between highest and lowest decrease between the models is in January with 70 %, the smallest in June with 45 %.

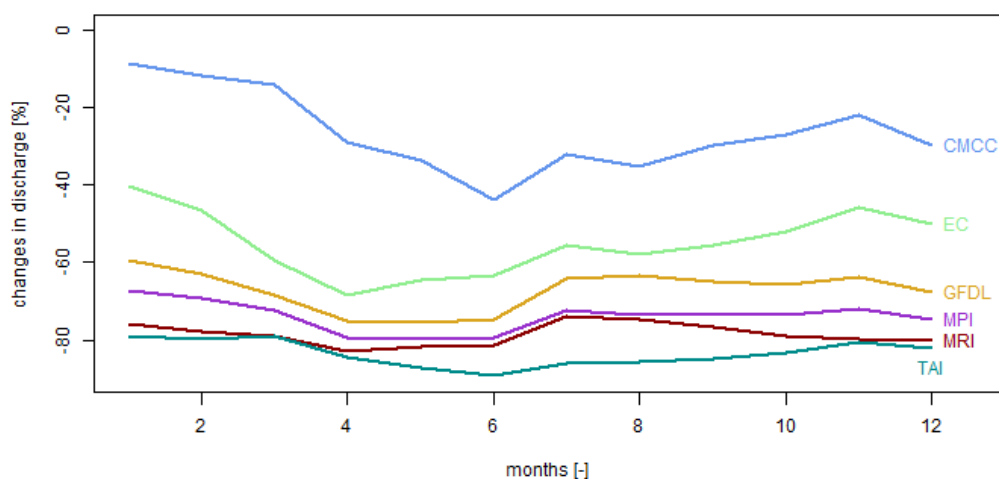


Fig. 4.18: Projections of seasonal runoff changes estimated from climate scenarios representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1991-2000 and a 30-year historical period for reference.

SSP 585 as can be seen in figure 4.19 leads to an increase in discharges for model CMCC in January and November of 12 and 0.3 % respectively. In the other months CMCC is the model which leads to the smallest change in discharge with values up to -36 % for February to October and -6 % for December. From January to July the MRI leads to the highest decreases in discharge showing values between -87 and -81 %. The rest of the year the TAI model results in the highest changes in discharge with values between -83 and -81 %. The models mostly follow similar patterns. The highest increase in discharge is in January for the CMCC, while the highest decrease in discharge for the CMCC is in June with -36 %. The highest decrease overall is in April with -87 %. The biggest differences between the different climate models are in January with 92 %, the smallest difference in June with 50 %.

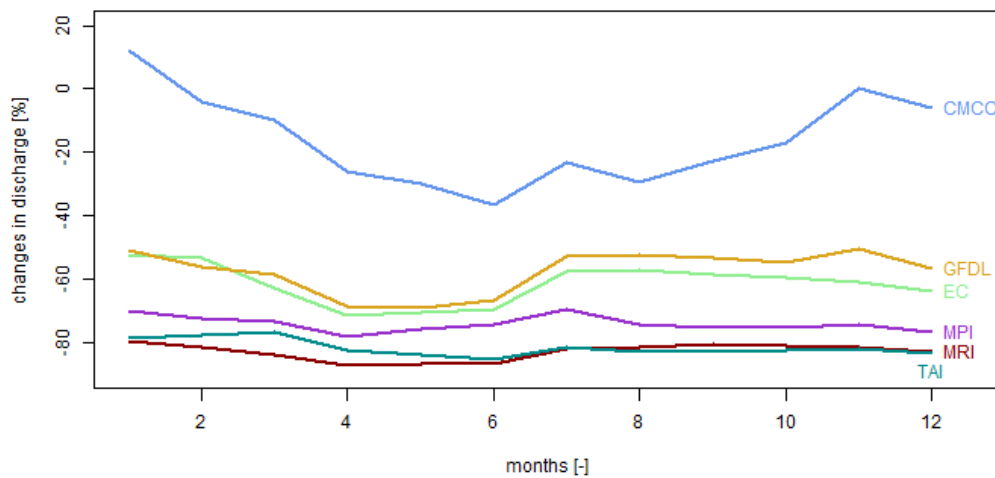


Fig. 4.19: Projections of seasonal runoff changes estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1991-2000 and a 30-year historical period for reference.

Generally, it can be said that the CMCC model tends to lead to the highest increases and lowest decreases in discharge, the TAI and MRI model to the highest decreases. This however is a pattern that is not shared by the SSP 126 pathway. All the models except the CMCC predict a decrease in discharges by between -90 and -40 % for SSPs 245, 370 and 585. The smallest differences between the models is in June most of the time, the highest decrease in discharge from April to June. The highest increase or lowest decrease often is in January, August or November, the biggest differences between the models in January.

The following figure 4.20 shows the predictions of change in seasonal discharge for the different climate models compared to a 10-year historical period for the SSP 585 and calibration variant distributed 91. A similar pattern as for the 30-year period can be seen, however the decreases tend to be smaller by approximately 20 % and for the CMCC model the increases tend to be bigger by up to nearly 50 %. Also, the trend towards the end of the year is towards less decrease or more increase instead of towards more decrease like in comparison with the 30-year historical period. Similar trends can be seen for the other SSP pathways.

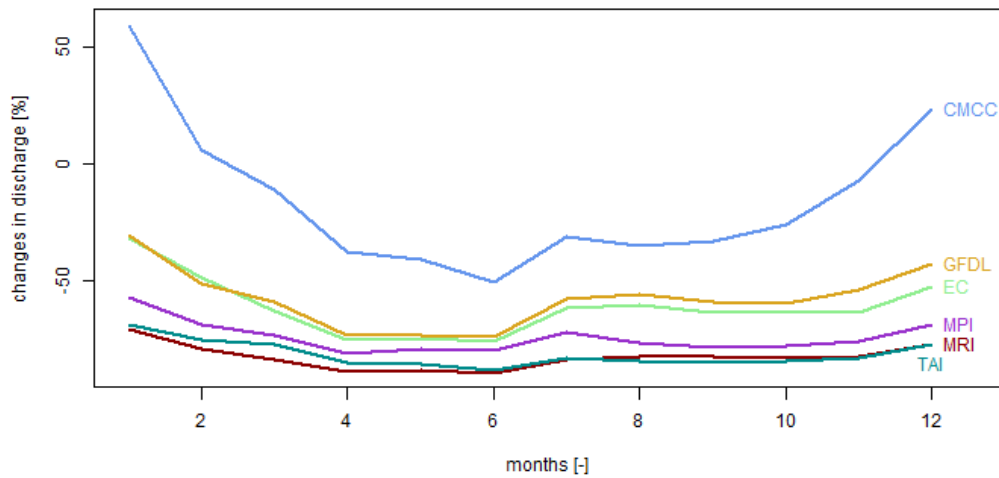


Fig. 4.20: Projections of seasonal runoff changes estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1991-2000 and a 10-year historical period for reference.

4.2.2 Comparison of annual data

The following figure 4.21 shows the medians for the annual changes in discharge of the climate models for the different SSP pathways. SSP 126 has medians between approximately -10 and 10 %. CMCC and EC show a median decrease, while the other models result in an increase, with MRI increasing the most. The variability of the changes in discharge over the 30-year period seems to be similar for the various models.

SSP 245 projects a median decrease in discharge for all models aside CMCC, which has a median of about 5 %. The TAI model has the highest median decrease in discharge of approximately -80 %. TAI and MRI show the littlest variability, CMCC the biggest. SSP 370 leads to similar findings, only with CMCC also having a median decrease of discharge of around -20 %.

SSP 585 shows a median decrease in discharge for all models. The CMCC has the least decrease with approximately -15 % and the biggest variability. The MRI model has the highest median decrease with about -80 % and the smallest variability.

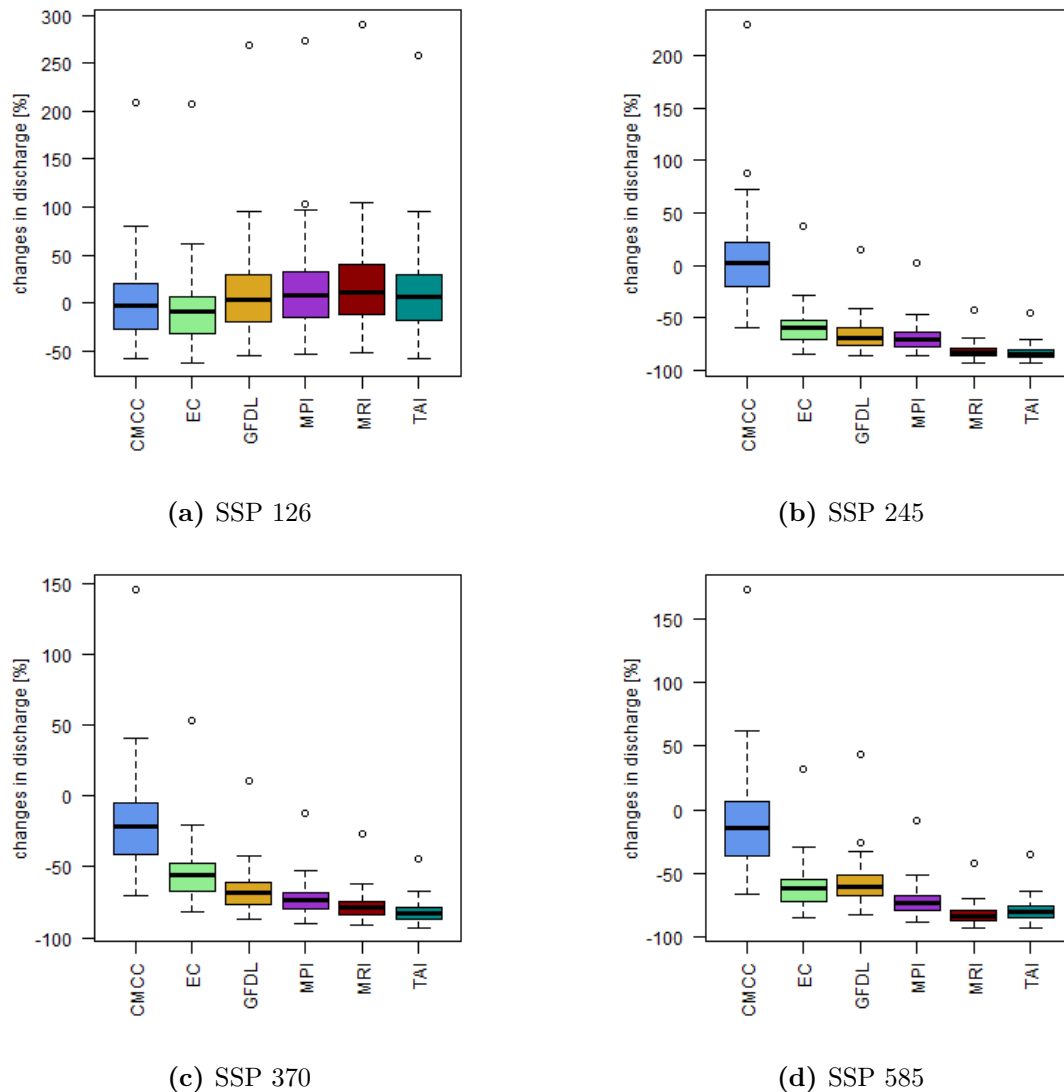


Fig. 4.21: Distribution of changes for annual mean discharges over 30 years compared to historical period for calibration variant distributed in period 1991-2000. Panel (a) shows sustainable and green shared socioeconomic pathways (SSP126), (b) the medium pathway (SSP245), (c) regional rivalry (SSP370) and (d) fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins is 20.

Altogether it can be said that the CMCC leads to the least changes in discharge for all SSP pathways except SSP 126. The other models most likely lead to decreases in discharge between -80 and -50 %. The changes for SSP 126 are a lot smaller and show tendencies towards a slight increase.

4.3 Uncertainty of hydrological projections

4.3.1 Comparison of seasonal data

Figures were created to show the variability and uncertainty in the predictions of changes in discharge in percent. For that a 30-year historical period as well as a 10-year historical period as further comparison are used. The following paragraphs show several diagrams for the seasonal changes in discharge. Further information can be found in the attachments in chapter 6.4.1. The depicted values can be seen in detail in chapter 6.3.1.

CMCC

The CMCC model for the 30-year period for SSP 126 as shown in figure 4.22 leads to an increase in discharges in winter of up to nearly 38 % and a decrease in summer of up to nearly -35 %. The decrease in July between -10 and -17 % is less than in June and August. The highest increase is in January. The biggest variability between the calibration variants is in November, with values between 12 and 28 %, the smallest in June, which displays values between -35 and -30 %. SSP 585 leads to similar findings, however the highest increase in discharge is smaller with around 20 % and the highest decrease is bigger with around -37 %. The biggest variability is in December with values between -12 and 4 %.

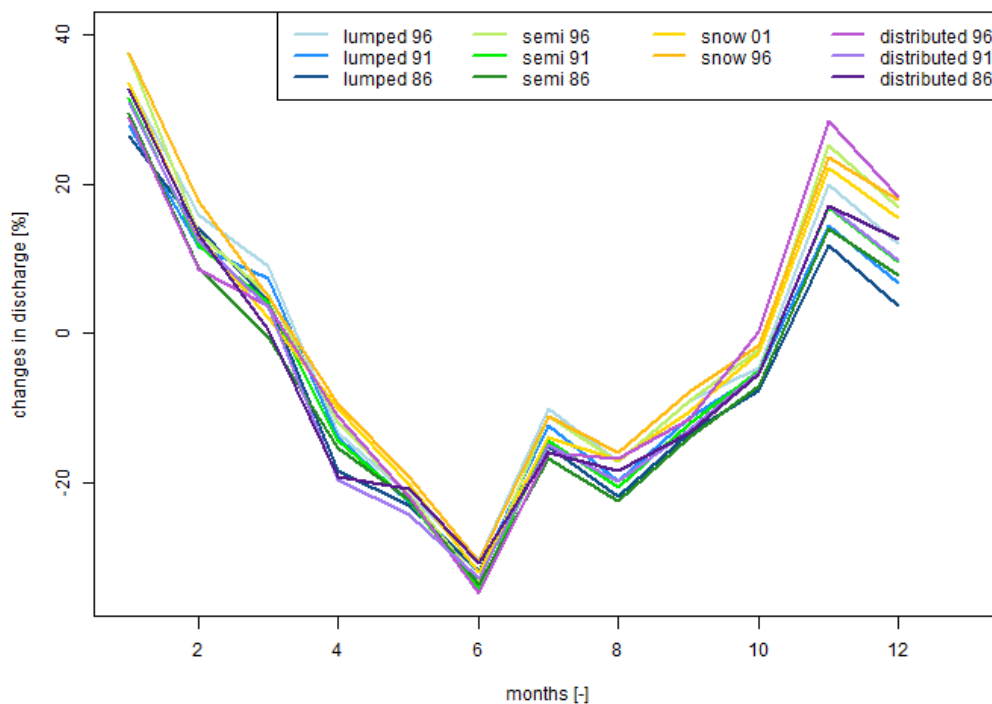


Fig. 4.22: Projections of seasonal runoff changes estimated from the CMCC climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

For SSP 245 the variant distributed 96 leads to less decrease in August compared to July with values of -1 and -6 % respectively. This can be seen in figure 4.23. Aside from that, the same general findings as for SSP 126 and 585 apply.

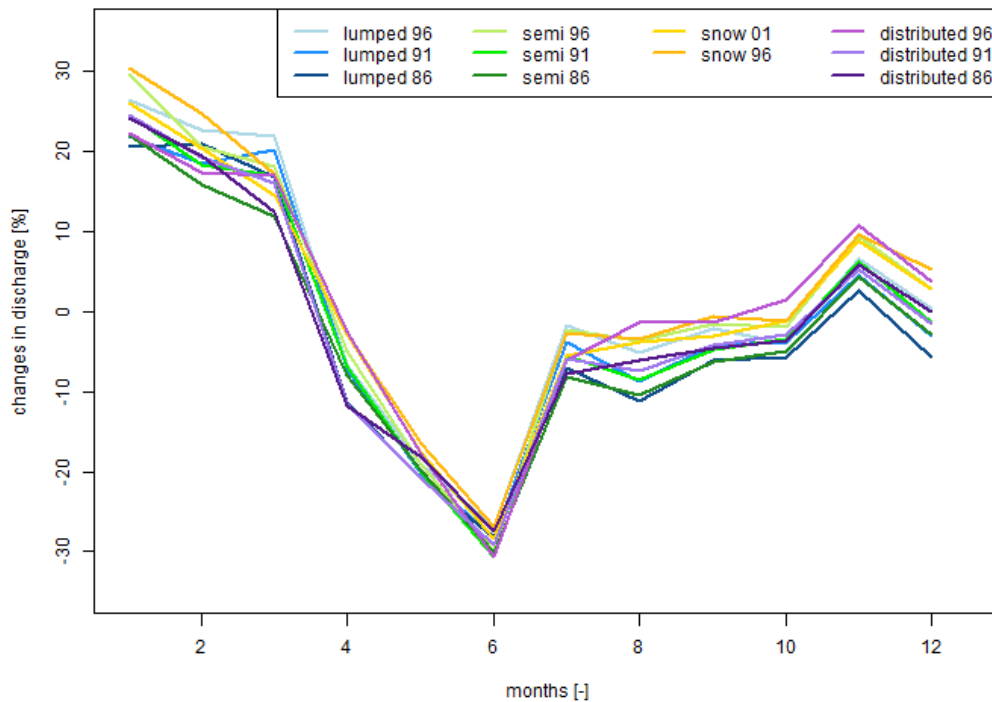


Fig. 4.23: Projections of seasonal runoff changes estimated from the CMCC climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

SSP 370 leads to a decrease of discharge for the whole year, with the highest decrease of -44 % being in June, followed by August with around -38 to -30 %, as shown in figure 4.24. The smallest decreases are in January, February and November with between -16 and -1 %, -20 and -5 % and -25 and -13 % respectively. The biggest variability is once more in January, February and December with differences in values of around 14 %, while the smallest is in June with approximately 7 % differences between the values.

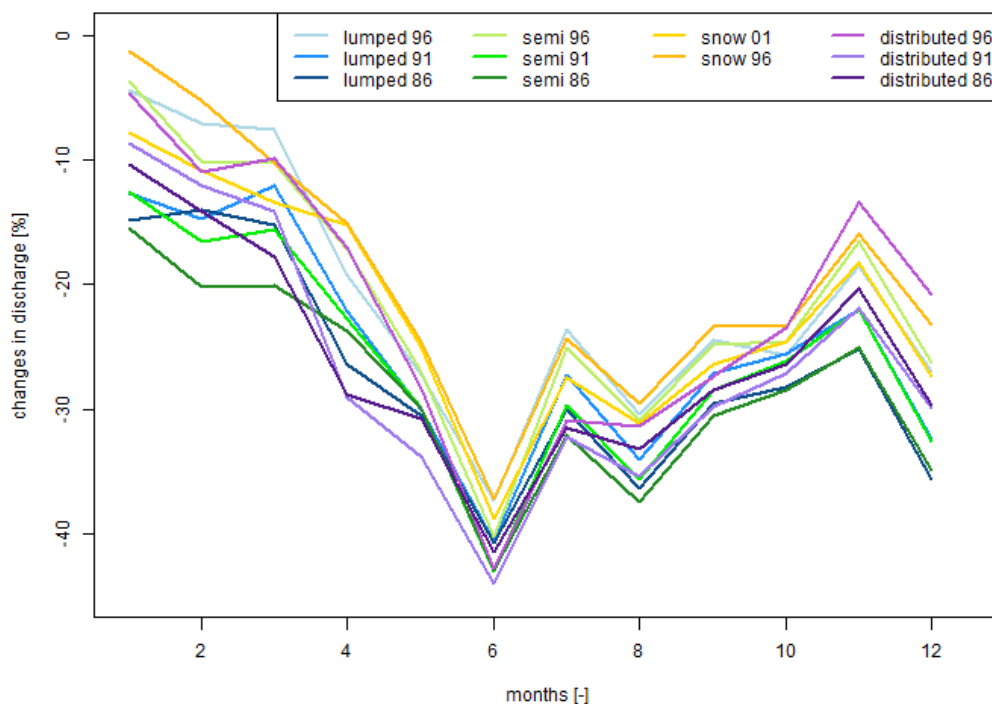


Fig. 4.24: Projections of seasonal runoff changes estimated from the CMCC climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

The projections for the CMCC model generally show the highest increase in discharge in January to February and in November. The highest decrease is in June, as is the smallest variability. The highest variability is most often towards the end of the year.

EC

For the 30-year period for SSP 126 the EC model shows an increase of discharge of up to 33 % in January and February and a decrease of up to -32 % for the rest of the year, besides December as can be seen in figure 4.25. In December it is unclear if an increase or decrease will occur, with values between -13 and 4 %. The highest decrease is in the months April to June depending on the model. The smallest variability is once again in June with 6 % between the values and the biggest variability is in January with 21 %.

The diagram for SSP 245 shows the same patterns as SSP 126, the only difference being the location on the y-axis. The whole year shows a decrease in discharge, the smallest being in January.

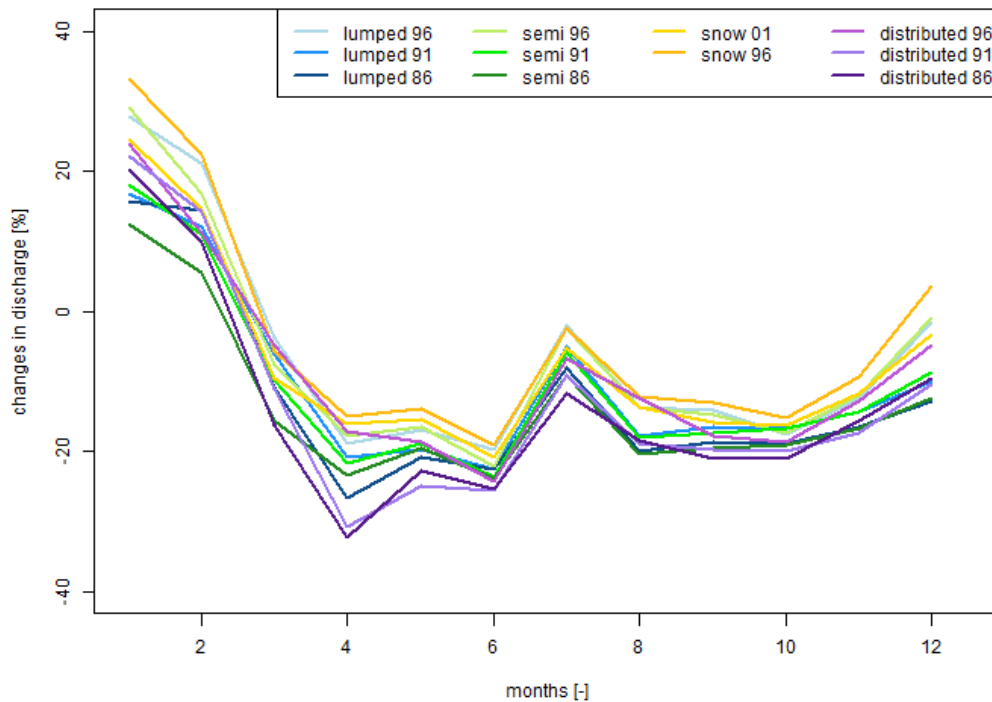


Fig. 4.25: Projections of seasonal runoff changes estimated from the EC climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

SSP 370 leads to the same findings as SSP 245, only the change in discharge in November with values from -47 to -41 % and December with -52 to -43 % being much smaller than in July with -56 to -53 %. This is shown in figure 4.26

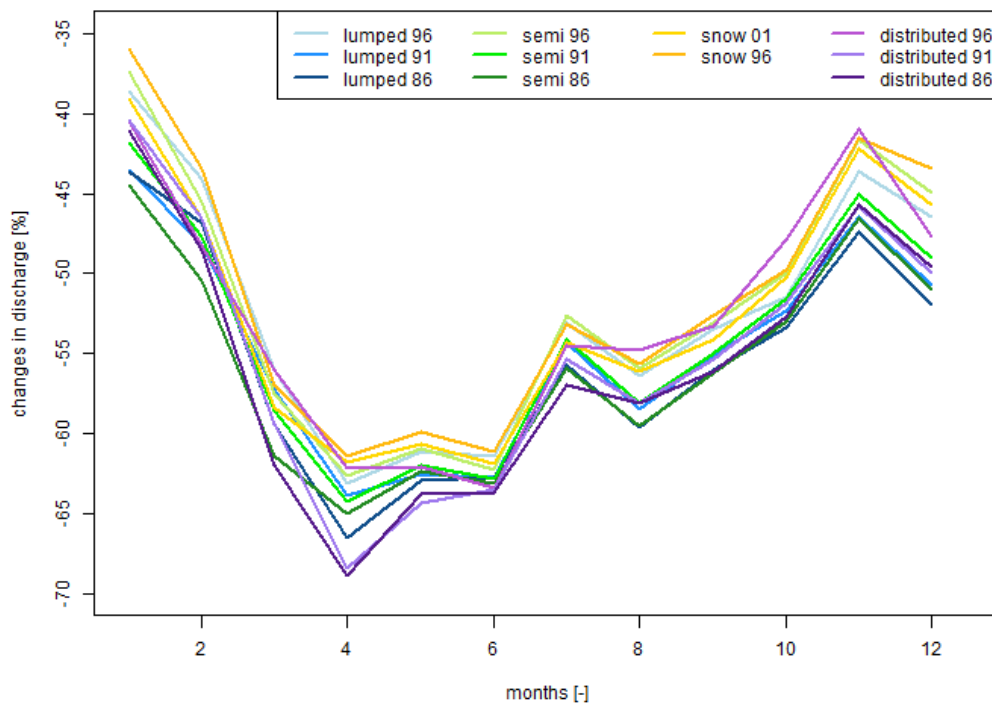


Fig. 4.26: Projections of seasonal runoff changes estimated from the EC climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

The SSP 585 has the smallest decrease in discharge in January, February, July and August with values of between -59 and -47 % as shown in 4.27. The highest decrease is from April to June, which display values between -72 and -64 %. The smallest variability is in June with differences in discharges of around 4 %, while the biggest is in January and February with 9 % and 8 % respectively.

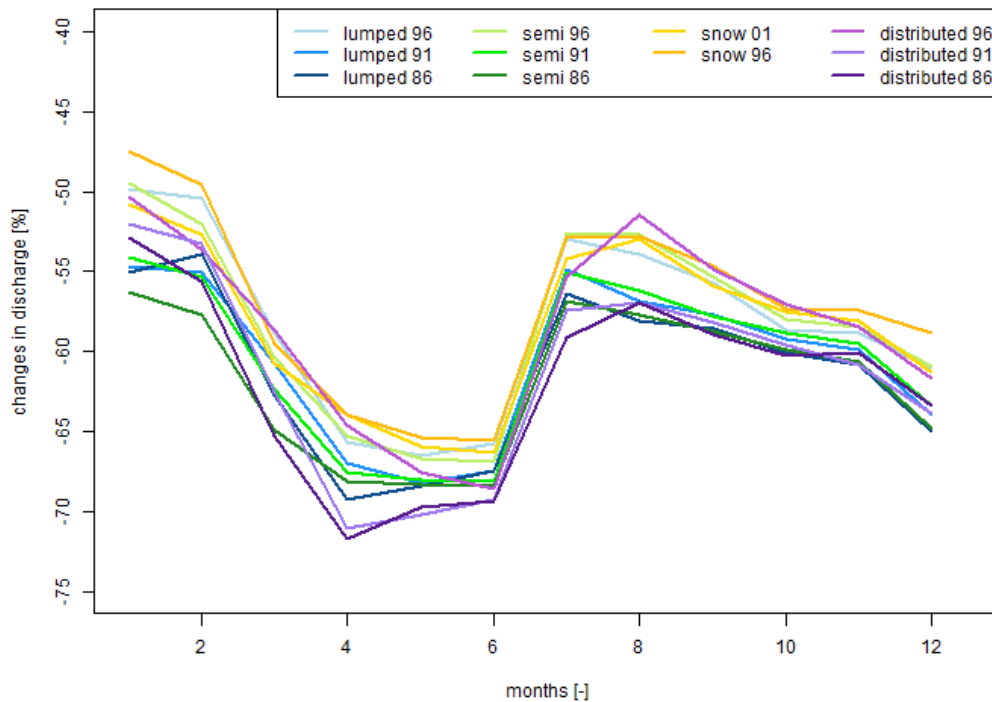


Fig. 4.27: Projections of seasonal runoff changes estimated from the EC climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

The EC model usually shows the highest increase or smallest decrease in discharge in January to February. The highest decrease is in April to June. June has the smallest variability, while the highest variability is often in January or April.

GFDL

Figure 4.28 for the climate model GFDL and pathway SSP 126 shows an increase in discharge for most months. For February, April and May it is unclear if there will be an increase or decrease because the different calibration variants indicate different outcomes with values between -11 and 7 %. The only clear decrease presents itself in June, which also shows the smallest variability, displaying values between -5 and -3 %. The biggest variability is in April with differences in values of about 16 %, the biggest increase in discharge in July with between 24 and 31 %.

SSP 585 shows the same patterns as SSP 126 but located further down the y-axis and only showing a decrease, with April to June having the highest decrease in discharge with values between -69 and -66 %. The smallest decreases are in January, August and November, displaying values between -54 and -48 %.

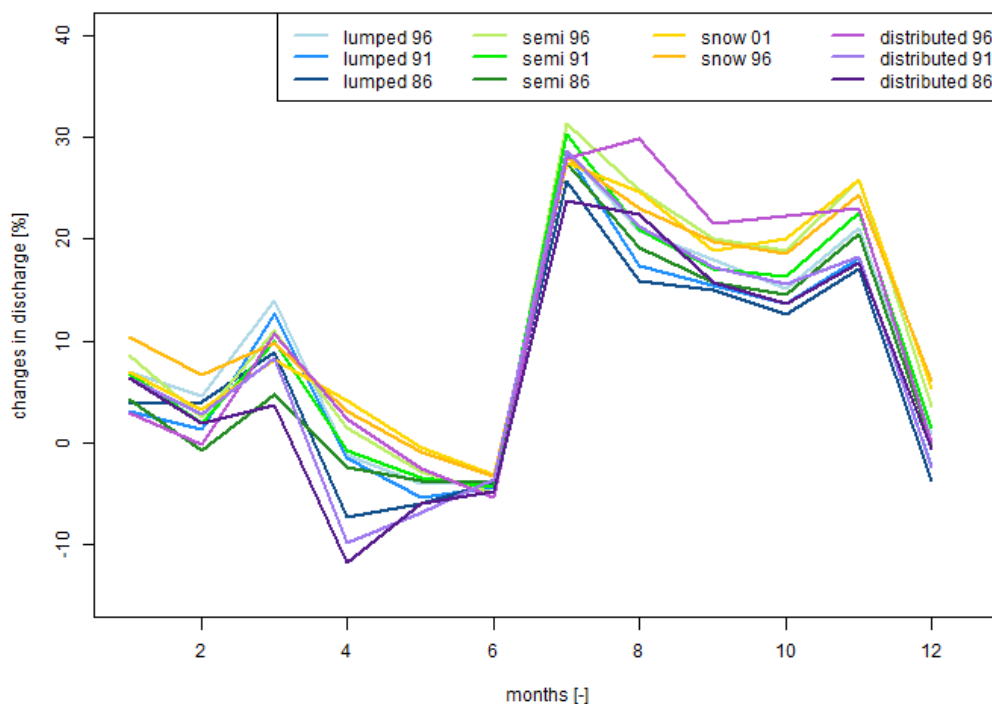


Fig. 4.28: Projections of seasonal runoff changes estimated from the GFDL climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

SSP 245 brings about a decrease in discharge, the biggest being between -79 and -75 % in April and May as shown in 4.29. The smallest decrease is from August to November, displaying values from -58 to -51 %. The smallest variability is in June with differences of approximately 2 % between values, the largest from August to November, showing differences of 4 to 6 %.

SSP 370 leads to similar changes in the discharge as SSP 245, with the only difference being that the smallest decrease of -61 to -58 % is in January and the largest variability of approximately 5 % is in April. Also, September and October have a larger change in discharge with -66 to -64 % than August and November with values of -64 to -61 %.

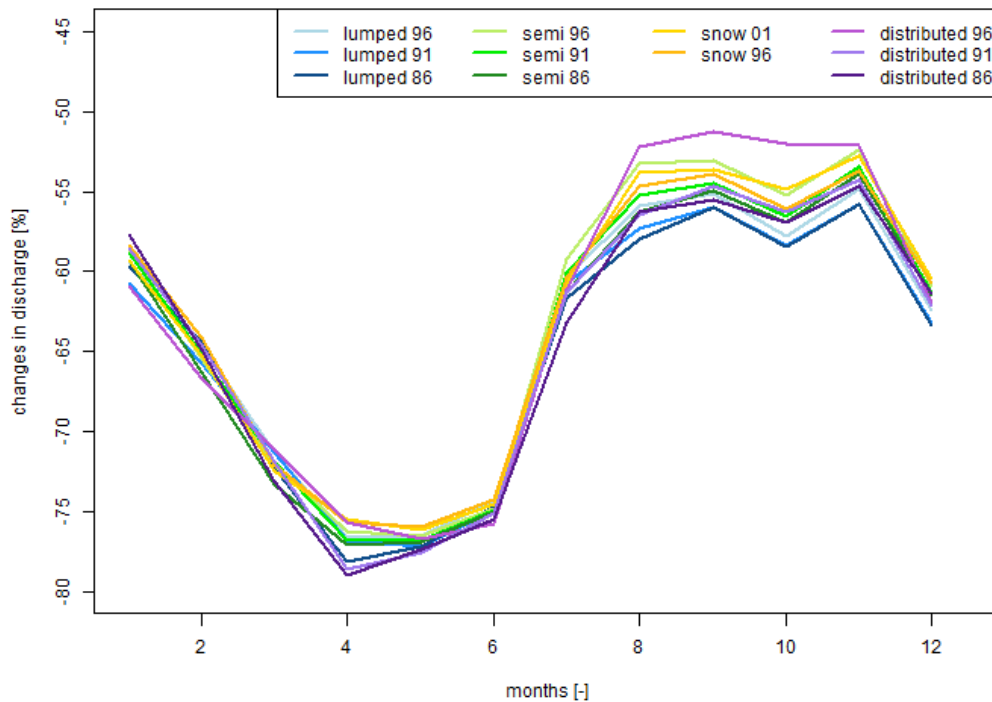


Fig. 4.29: Projections of seasonal runoff changes estimated from the GFDL climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

For the GFDL model the highest increase or smallest decrease in discharge is usually in January or from July to November. The highest decrease is from April to June. June also has the smallest variability. The highest variability is usually either in April or from August to October.

MPI

The MPI model predicts mostly an increase in discharges for SSP 126 for the 30-year period as can be seen in figure 4.30. Only during the months April, May and December, which display values between -8 and 4 %, a decrease could be possible depending on the calibration variant. The highest increase of 28 to 37 % is in July, the highest variability in August with a range of 16 %, the smallest variability of 3 % is in June.

SSP 585 leads to similar projections as SSP 126. The main difference is the location on the y-axis. SSP 585 leads to a decrease in discharge throughout the year.

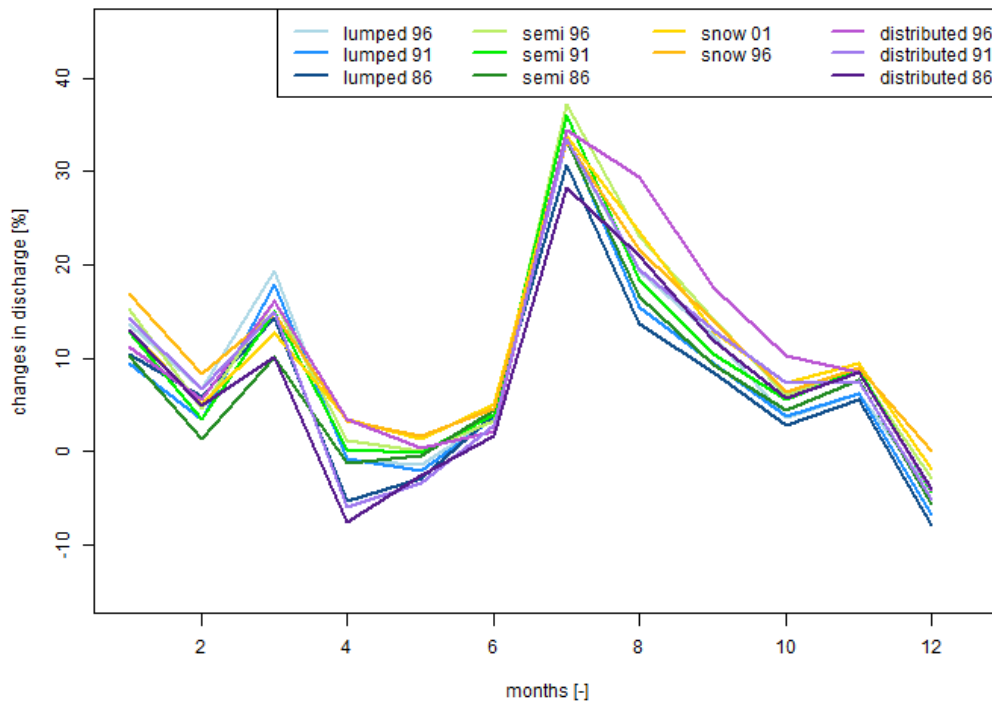


Fig. 4.30: Projections of seasonal runoff changes estimated from the MPI climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

For SSP 245 a decrease in discharge is predicted as shown in figure 4.31. The smallest decrease of -62 to -57 % is in November, the highest decrease of -79 to -78 % in June. June once again shows the smallest variability with less than 1 %, October the biggest with 7 %.

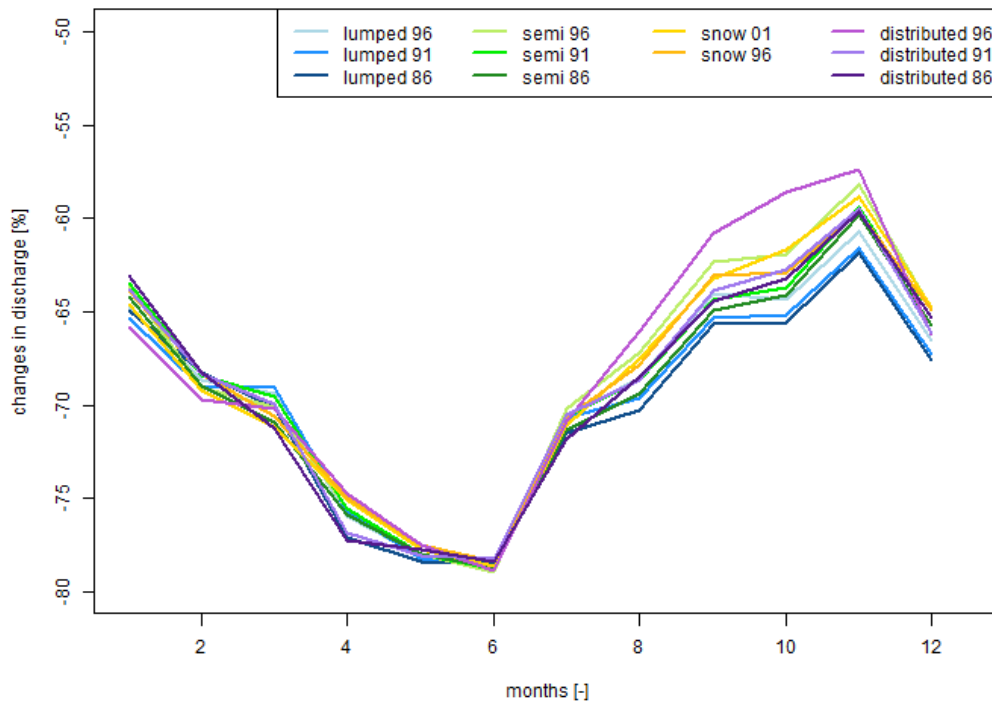


Fig. 4.31: Projections of seasonal runoff changes estimated from the MPI climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

SSP 370 shows the smallest decrease of discharges in January with values between -69 and -67 %, the biggest in April to June, displaying values between -80 and -77 % as indicated in figure 4.32. From July to December the changes decrease again, often showing values between -74 and -70 %. The smallest variability of 1 % is in June, the biggest with 3 % in April and August.

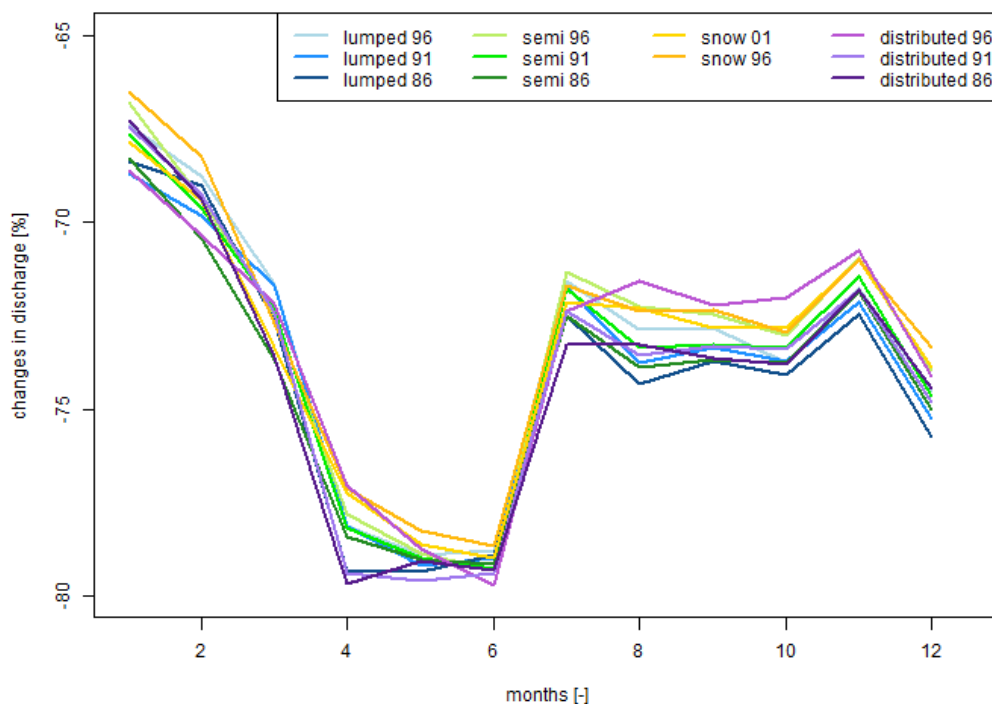


Fig. 4.32: Projections of seasonal runoff changes estimated from the MPI climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

For the MPI model the highest increases or smallest decreases in discharge are usually in January, July or November. The highest decreases are often displayed in April to June, however December also sometimes has high declines in discharge. June has the smallest variability, April and August generally the highest.

MRI

The projections for the MRI show similarities to the GFDL model. For SSP 126 for the 30-year historical period most of the year leads to an increase in discharge, the highest being from July to September with values of 29 to 48 %. This can be seen in figure 4.33. The only months leading to a decrease are April to June with a -10 to -1 % change in discharge. June once again shows the least variability with only 2 % difference between the calibration variants, August the most with 16 % difference.

SSP 370 is similar to SSP 126, the only difference being the location on the y-axis and the decrease in discharge for the whole year.

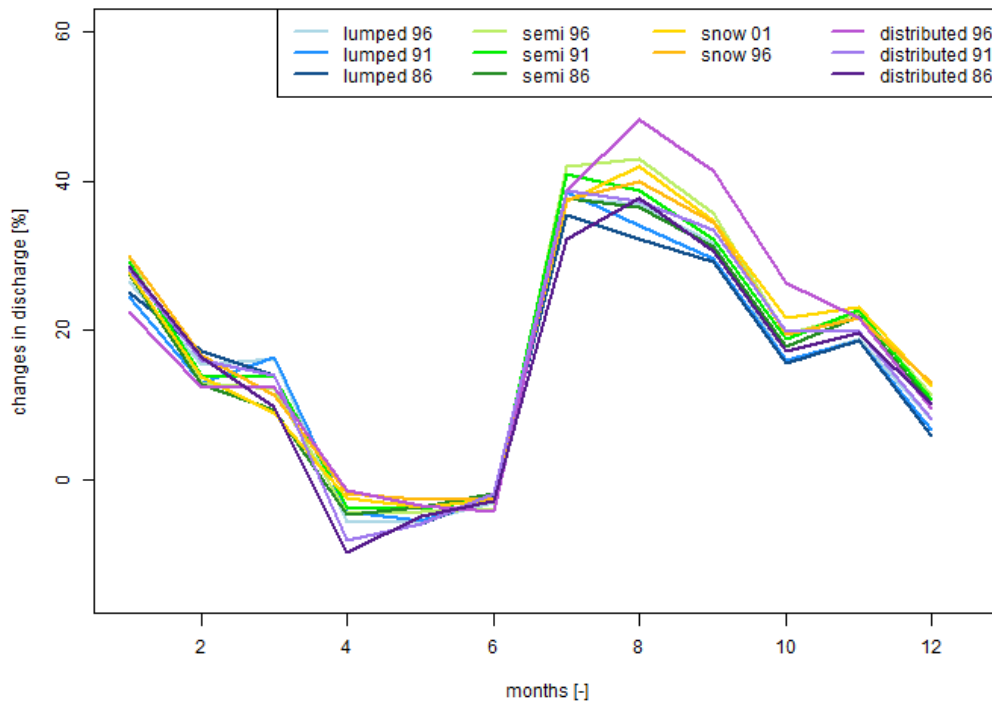


Fig. 4.33: Projections of seasonal runoff changes estimated from the MRI climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

The projections for SSP 245 show the smallest decrease in discharge of -81 to -79 % for July to September and the highest decrease in April to June with -86 to -84 % as can be seen in figure 4.34. June has the smallest variability with 1 %, March and July the biggest with 2 %.

SSP 585 leads to similar findings as SSP 245, the only difference being that January also leads to the smallest decrease in discharge and the biggest variability being in July, October and December.

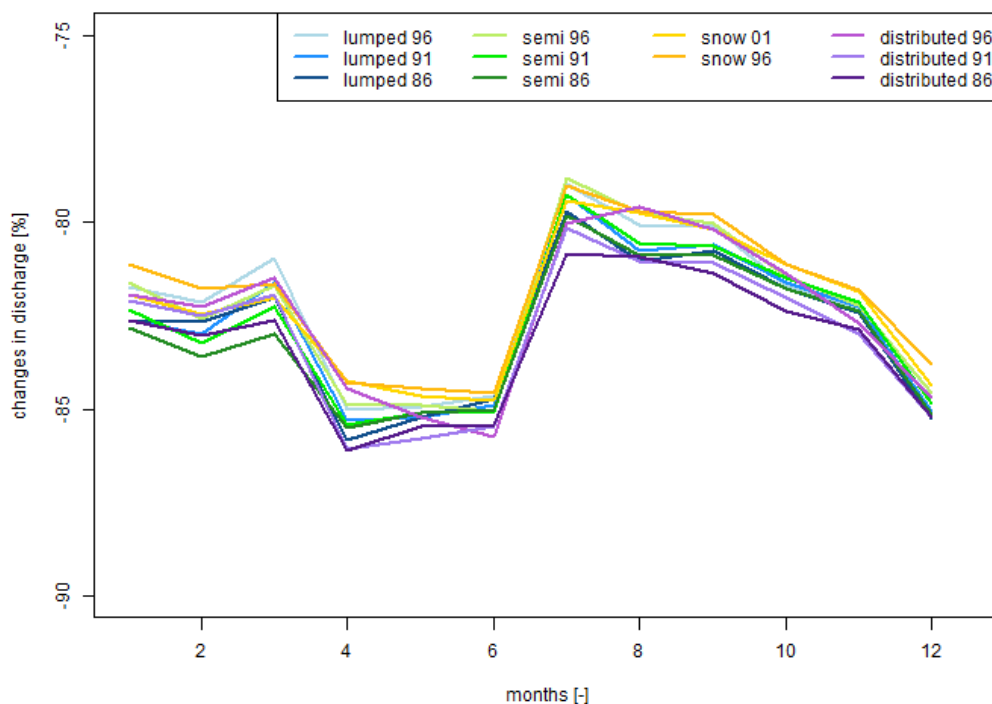


Fig. 4.34: Projections of seasonal runoff changes estimated from the MRI climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

The MRI model generally leads to the highest increases and smallest decreases being in January or from July to November. The highest declines in discharge are usually from April to June. June once more has the smallest variability. The month with the highest variability is not so easy to determine, however often times the highest variability is shown in August.

TAI

When looking at the projections for the TAI model with regards to SSP 126 for the 30-year period in figure 4.35 there is an increase in discharge for January to March, and a decrease in May to June and August to October. For the other months it depends on the calibration variants. The highest decrease in discharge of -20 to -15 % and smallest variability of 5 % is in June, the biggest increase of 17 to 31 % is in March. The biggest variability of 17 % is in December.

SSP 245 leads to a mostly similar diagram, only moved downwards on the y-axis. The smallest decrease of between -84 to -82 % is in March, July and November, the biggest variability is in August with a difference of 2 % between calibration variants.

SSP 585 also shows similar findings as SSP 126, only changes being the location on the y-axis with a decrease for the whole year and the smallest decrease of -79 to -76 % being in January to March. The biggest variability of 4 % is in December.

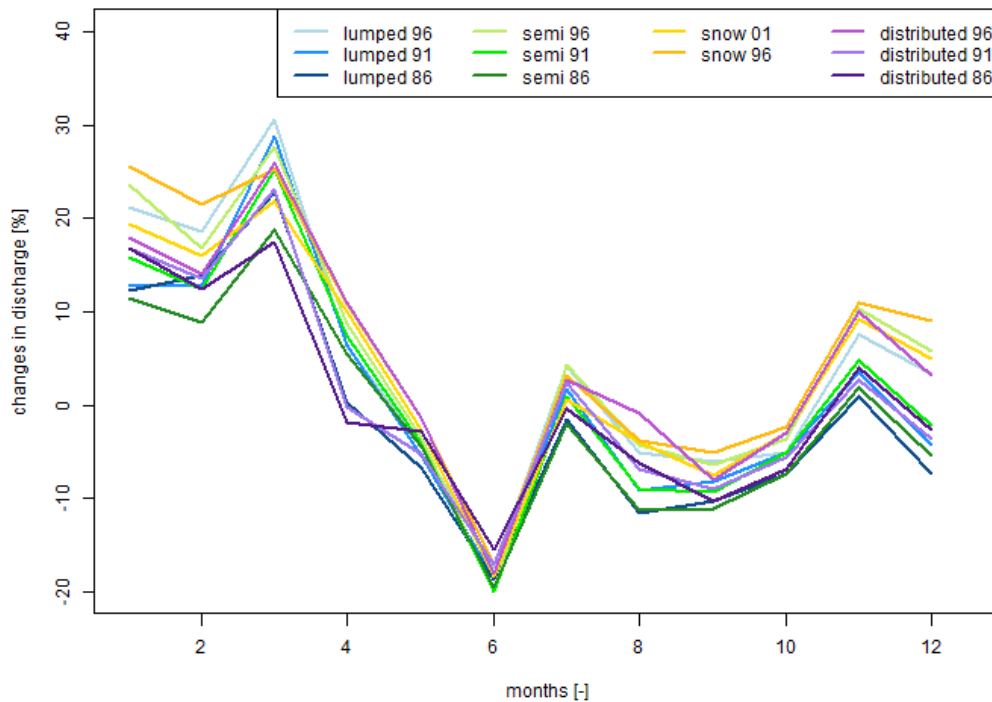


Fig. 4.35: Projections of seasonal runoff changes estimated from the TAI climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

The projections for SSP 370 as shown in figure 4.36 display the highest decrease of approximately -90 to -89 % in June and the smallest variability of about 1 % in May. The smallest decrease is in January to March and in November with values between -81 and -77 %. The highest variability of 3 % is in November to December.

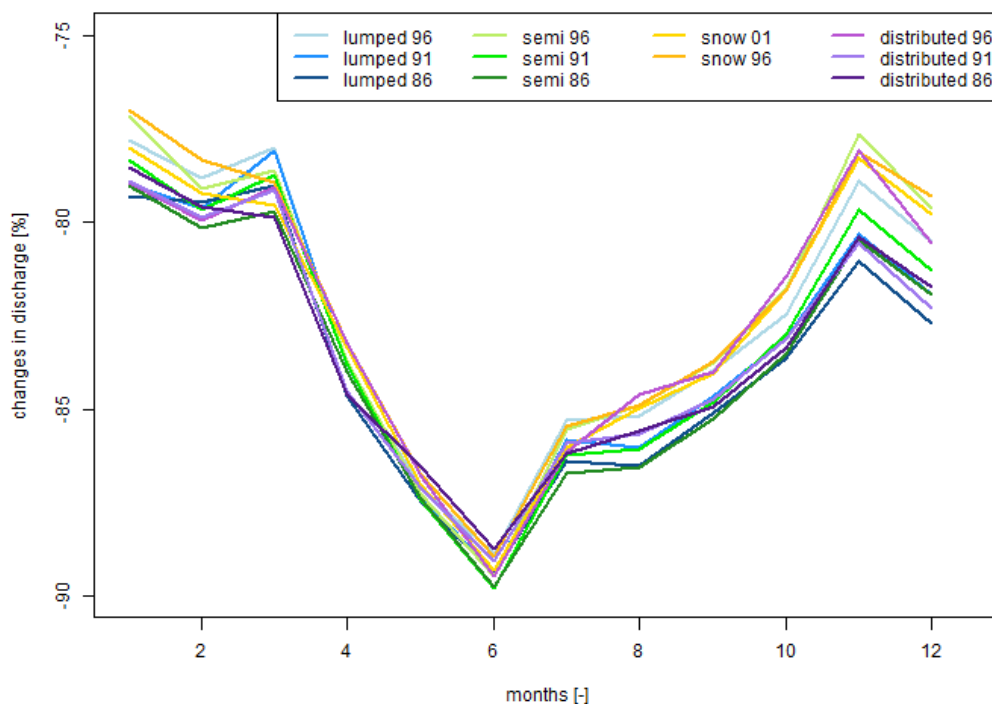


Fig. 4.36: Projections of seasonal runoff changes estimated from the TAI climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

The TAI climate model indicates the highest decrease in discharge in June. The smallest decrease or highest increase usually is at the beginning of the year from January to March. The highest variability often shows itself at the beginning or end of the year, the smallest is in June.

Comparison between projections for 30-year period

While for the CMCC model an increase in discharge for at least a few months can be seen for SSP 126, 245 and 585, all other models only show an increase for SSP 126. So, developments along the pathways of SSP 245, SSP 370 and SSP 585 most likely lead to a decrease in discharge throughout the year, while a development more alike SSP 126 may lead to increases and decreases depending on the month. The highest increase or smallest decrease depending on the climate model is indicated to happen for January or July most of the time. The highest decrease is usually in April to June. There is no trend for the highest variability. June has the smallest variability.

SSP 245 shows the highest increase or smallest decrease either at the beginning of the year in January to March or for August to November. The highest decrease is shown in April to June. The months of highest variability are different for the different projections. The smallest variability is in June.

For SSP 370 the diagrams generally show the highest increase or smallest decrease of the year in either January to March or July to November. For some models the change in discharge for December is also small compared to the other months. The highest change in discharge is once more typically in April to June. The variability is often high towards the end of the year, however sometimes also in April or August. June has the smallest variability.

The projections for SSP 585 once again often show the highest decrease of discharge in the months April to June, with June also having the smallest variability. The smallest decreases and highest increases in discharge are generally in January and from July to November. The highest variability does not follow an observable pattern.

In terms of variability, it can be seen that the smallest variability between the different calibration variants is in June most of the time. June is also often one of the months with the highest decrease in discharge, if not the highest. Other months with often high decreases of discharge are April and May. The smallest decrease or highest increase of discharge is often at the beginning of the year or during late summer to autumn, especially in November. As for the highest variability, there are fewer significant trends, however often times the highest variability is towards the beginning or end of the year or in April or August. The biggest differences between biggest and smallest variability are for SSP 126 and for the CMCC model. The climate models MPI, MRI and TAI generally lead to the smallest variability.

Overall, it can be said that in the beginning of the year there is usually an increase in discharge or a smaller decrease. The discharge then generally decreases further towards April to June. Quite often the change in discharge for July is significantly less than for June. In late summer or early autumn there usually is again a short larger decrease in discharge compared to July, before often times leading to a smaller decrease in November. December again shows a trend towards more decrease in discharge.

Comparison 30-year historical period to 10-year historical period

The 10-year historical period leads to very uniform figures for each climate scenario using the different SSP goals. Further information can be seen in the attachments in chapter 6.4.1. Generally, the 10-year historical period leads to bigger differences between the changes in discharge due to the calibration variants than the 30-year period.

For the 10-year period as shown in figure 4.37 for the GFDL model and the SSP245 pathway the highest increase in discharge or smallest decrease in discharge is typically in January. There is a further decrease in discharge until it reaches the highest decrease in April or June. Like in the 30-year historical period the decrease is smaller for July and often times becomes bigger again during the autumn. The discharge changes then get smaller again towards December.

The projections show a range of the discharge changes in percent over the year of between 102 % and 155 % for the CMCC model for the different SSPs. It is the model with the biggest differences in change over the year between the SSPs. The model with the smallest differences in change is the MRI model for most of the SSPs, with ranges of change between 17 and 122 %. Generally, the ranges of change are the biggest for SSP 126, and the smallest for SSP 370.

Once again, the projections for SSP 126 and the CMCC model show the biggest variability. The climate models MPI, MRI and TAI generally lead to the smallest variability.

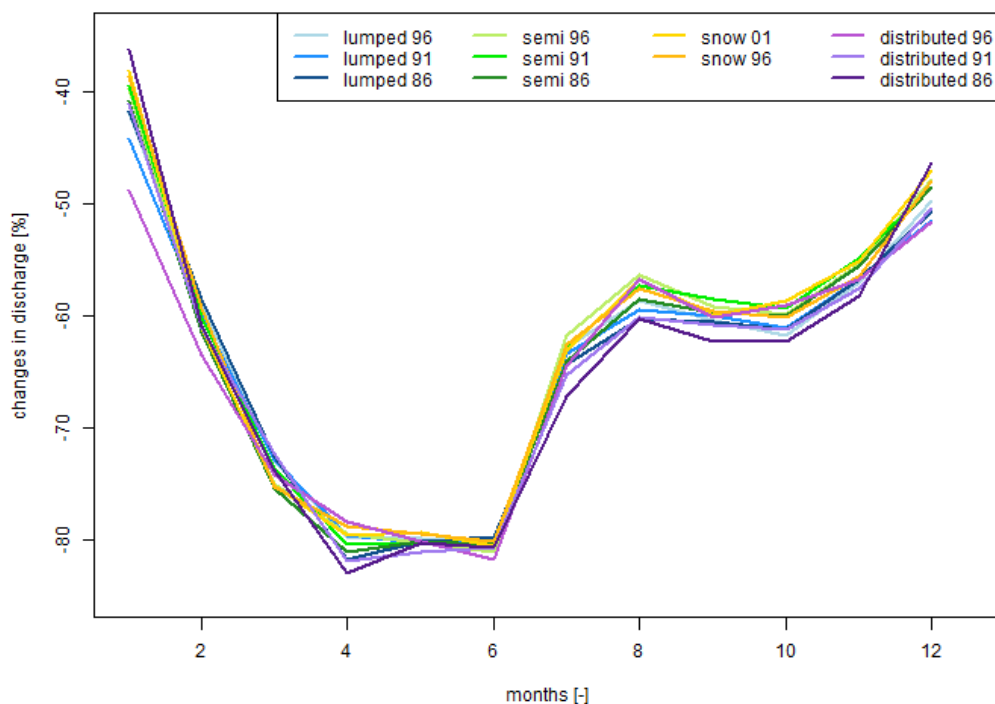


Fig. 4.37: Projections of seasonal runoff changes estimated from the GFDL climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

Range of changes in discharge for calibration variants

The following tables 4.1 to 4.4 show the variability of the calibration variants for the different SSPs. SSP 126 leads to a variability between 11.65 and 65.01 %, usually showing the smallest values in February with the minimum being for calibration variant lumped 91 and biggest ranges for August, with the maximum being for distributed 96.

SSP 245 displays a variability between 55.89 and 113.05 %. Most of the time the smallest ranges are in June, with the smallest variability being for variant semi-distributed 91 and the widest ranges in January with snow 96 leading to the biggest variability of 113.05 %. It can generally be seen that the winter months tend to have bigger variabilities than the summer months.

For SSP 370 the differences in variability between the months is smaller than for SSP 245. Also, while most winter months tend to show the bigger variabilities, December has some of the smallest ones. June once again shows most of the smallest ranges, with the minimum of 45.06 % being for distributed 91, while January usually has the widest ranges with the maximum of 75.81 % for snow 96.

SSP 585 once again leads to most bigger variabilities being in winter, with the widest ranges usually in January and snow 96 leading to the maximum of 98.38 %. June once again has most of the smallest ranges, with distributed 96 leading to the minimum of 49.27 %.

All in all, it can be said that SSP 245, SSP 370 and SSP 585 lead to similar findings for the different calibration variants, while SSP 126 shows a different pattern. The smallest variability is shown by SSP 126, followed by SSP 370. SSP 245 has the biggest range of variability. Calibration

variant snow 96 leads most often to the widest range of values. It is not possible to see a similar pattern for the smallest variability in terms of calibration variants. There seems to be patterns due to the months, but less so due to the calibration variants.

Tab. 4.1: Variability of calibration variants for sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.) [%]

calibration variant	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
lumped 86	22.53	13.15	33.67	26.83	20.21	35.68	50.77	54.05	47.73	34.45	35.15	18.66
lumped 91	24.74	11.66	34.82	27.21	20.60	35.52	50.91	53.89	46.02	32.70	33.02	16.76
lumped 96	26.28	16.44	34.16	25.22	20.20	34.02	47.94	53.91	45.78	33.43	33.34	16.21
semi 86	25.08	13.65	34.42	28.81	21.77	38.23	54.57	59.05	50.72	36.98	38.53	22.42
semi 91	24.57	12.05	35.06	29.09	22.32	38.22	55.31	59.47	49.51	35.57	36.89	19.32
semi 96	28.74	14.20	35.21	26.52	21.69	36.69	53.20	60.07	50.48	36.73	37.84	19.73
snow 96	27.14	15.77	30.98	25.78	20.85	35.14	48.49	56.03	47.46	34.52	33.71	17.89
snow 01	26.67	12.67	31.36	26.14	21.49	36.94	51.40	59.10	50.40	37.92	37.57	18.72
distr 86	26.40	14.48	33.80	30.46	20.29	32.38	48.28	56.19	51.56	38.22	35.30	22.09
distr 91	24.54	13.21	34.10	30.67	21.52	35.59	53.66	57.10	53.26	39.69	37.23	20.18
distr 96	25.90	14.21	30.61	28.09	22.23	37.03	54.66	65.01	59.01	44.93	41.19	23.20

Tab. 4.2: Variability of calibration variants for the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.) [%]

calibration variant	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
lumped 86	104.89	105.47	99.96	74.48	64.39	58.11	76.29	73.84	78.62	78.71	86.49	80.91
lumped 91	106.26	103.35	102.69	78.11	64.98	58.05	78.93	75.76	80.20	80.27	88.05	83.20
lumped 96	109.84	106.62	104.03	78.29	65.88	59.22	80.59	78.59	81.72	79.75	89.65	85.96
semi 86	106.67	101.30	95.85	77.45	65.17	56.36	75.15	74.34	78.49	79.33	87.97	83.53
semi 91	108.66	103.46	100.14	78.54	65.01	55.89	77.32	75.88	79.66	80.56	89.41	84.64
semi 96	112.84	104.94	100.78	79.89	65.72	56.55	79.95	79.71	82.22	81.44	92.10	88.28
snow 96	113.05	108.42	100.06	81.68	67.88	59.12	79.85	79.92	82.97	82.15	92.11	90.06
snow 01	109.68	104.68	97.73	81.36	66.97	57.77	77.29	79.51	80.94	82.09	91.48	88.15
distr 86	108.26	104.24	96.36	74.38	67.26	59.05	75.80	78.19	80.03	80.56	89.30	86.20
distr 91	108.37	103.94	99.22	74.57	64.93	57.43	77.28	76.92	80.12	81.03	88.87	84.89
distr 96	106.11	101.77	99.64	81.91	67.37	55.96	76.72	81.60	82.33	84.32	93.53	89.39

Tab. 4.3: Variability of calibration variants for regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.) [%]

calibration variant	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
lumped 86	64.48	65.48	63.76	58.26	56.93	48.58	56.35	50.12	55.50	55.40	55.87	47.08
lumped 91	66.37	64.88	66.10	61.60	57.34	48.74	58.49	51.95	57.56	57.56	58.31	49.56
lumped 96	73.40	71.76	70.47	64.62	59.91	51.54	61.71	54.77	59.50	56.84	61.06	53.48
semi 86	63.52	60.02	59.66	60.25	57.45	46.76	54.56	49.03	54.72	55.04	55.34	46.93
semi 91	65.79	63.12	63.18	61.07	57.59	46.72	56.53	50.49	56.30	56.83	57.64	48.65
semi 96	73.51	69.03	68.46	66.56	60.32	49.18	60.47	54.04	58.98	57.17	62.64	53.39
snow 96	75.81	73.08	68.66	68.14	62.24	51.70	61.12	55.33	60.37	58.48	63.19	55.99
snow 01	70.20	68.36	66.19	68.17	61.99	50.45	58.56	53.78	57.61	57.22	60.79	52.45
distr 86	68.20	65.52	62.13	55.79	55.77	47.26	54.66	52.39	56.50	56.90	60.03	52.03
distr 91	70.29	67.87	65.00	55.50	53.31	45.06	53.71	50.25	54.92	55.97	58.64	52.32
distr 96	74.30	68.95	69.20	66.19	58.41	46.63	55.25	53.22	56.65	57.95	66.18	59.70

Tab. 4.4: Variability of calibration variants for fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.) [%]

calibration variant	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
lumped 86	87.67	77.05	73.69	62.57	58.32	52.37	61.16	54.52	61.93	65.12	78.94	71.50
lumped 91	89.18	75.97	76.38	65.68	58.77	52.37	63.19	56.16	63.85	67.38	81.38	74.57
lumped 96	95.33	80.60	78.43	66.87	60.07	53.70	64.99	57.94	65.52	67.04	85.25	79.96
semi 86	88.23	72.74	69.83	64.47	58.71	50.65	59.30	53.27	61.06	64.97	79.24	72.89
semi 91	90.33	74.91	73.28	64.99	58.54	50.24	61.15	54.64	62.65	66.82	81.44	74.85
semi 96	97.10	78.42	75.64	67.99	59.89	51.20	63.63	57.05	65.11	67.98	87.83	82.08
snow 96	98.38	82.27	75.49	70.04	62.03	53.64	64.45	58.61	66.52	69.25	88.01	84.43
snow 01	93.45	78.19	72.89	69.54	61.01	52.27	62.02	57.43	63.72	67.76	85.45	81.10
distr 86	91.61	77.64	71.37	61.69	59.58	52.47	59.16	54.74	60.54	65.69	83.30	78.20
distr 91	91.80	77.52	73.80	61.05	56.65	50.23	58.74	53.42	60.09	65.50	82.24	77.00
distr 96	92.76	77.39	75.20	68.22	59.14	49.27	58.14	55.33	61.31	69.08	91.64	85.46

Range of changes in discharge for climate models

In the following tables 4.5 to 4.8 the different variability of the climate models for the SSPs can be seen. SSP126 shows variabilities between 2.16 and 20.85 %. The minimum value is for model GFDL, the maximum for the EC model. It can also be seen that the trends between the months are less uniform compared to the variability ranges for the calibration variants. While for all models besides the EC the smallest variability is in June, the month of the biggest variability varies depending on the climate model, showing the biggest variability for the CMCC model in November, EC in January, GFDL in April, MPI and MRI in August and TAI in December.

For SSP 245 the biggest variability of 11.05 % for the CMCC model is in December, the smallest with a value of 0.58 % for the TAI model is in June. Once again, all climate models besides the EC have the smallest range in June, while the biggest variability for the climate models varies more in month, with the biggest variability for the CMCC model being in December, EC model in January, GFDL and MPI in October, MRI in July and TAI in August.

SSP 370 has the smallest variability of 0.64 % produced by the MRI model in November. The biggest variability of 14.91 % by the CMCC model is in February. While most models have the smallest range in June, for the CMCC, EC and TAI model the smallest variability is in October, November and May respectively. There is no consensus on the month with the biggest variability, with CMCC showing the widest range in February, EC in January, GFDL in April, MPI and MRI in August and TAI in November and December.

The range in variability for SSP 585 is from 0.80 % for the TAI model in May to 15.60 % for the CMCC model in December. Once again, most models have the smallest range in June. The EC models' smallest range is in October and the TAI models smallest range is in May. The three models CMCC, MRI and TAI show the biggest variability in December, while the EC model has the biggest variability in January, GFDL in August and MPI in April.

Generally, it can be said that SSP 245 has the smallest variability for the different climate models, followed by SSP 370 and SSP 585. SSP 126 leads to the biggest ranges. The smallest variability is most often in June for all models besides the EC model, which usually has the smallest variability in October. The CMCC model has its widest range mostly in the winter months, EC in January, MRI for all SSPs besides SSP 585 in the summer months and TAI for all SSPs besides SSP 245 in late autumn or early winter. For GFDL and MPI no patterns can be noted. The CMCC model most often leads to the biggest variability.

Compared to the variability depending on the different calibration variants it can be seen that there are not many consistencies. The SSP leading to the smallest variability for one leads to the biggest one for the other. The only similarity is that June leads to the smallest range most of the time.

Tab. 4.5: Variability of climate models for sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.) [%]

climate model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CMCC	11.17	9.11	9.57	10.08	5.14	4.43	6.68	6.47	6.06	7.93	16.61	14.68
EC	20.85	16.87	12.70	17.38	11.02	6.44	9.73	8.22	8.13	5.77	8.03	16.60
GFDL	7.47	7.49	10.24	15.89	6.35	2.16	7.50	14.01	6.55	9.59	8.89	9.77
MPI	7.47	6.98	9.37	11.10	5.04	3.33	8.95	15.77	8.98	7.46	3.78	7.87
MRI	7.66	4.82	7.64	8.30	3.16	2.39	9.68	16.19	12.08	10.77	4.42	7.17
TAI	14.06	12.68	13.06	12.85	5.39	4.62	6.31	10.68	5.94	5.16	10.10	16.53

Tab. 4.6: Variability of climate models for the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.) [%]

climate model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CMCC	9.82	8.92	9.98	9.27	4.26	3.77	6.37	9.85	5.67	7.09	8.20	11.04
EC	8.55	8.09	6.16	8.26	5.07	3.20	4.76	4.19	4.02	2.81	3.97	6.77
GFDL	3.24	2.55	2.23	3.48	1.62	1.53	3.96	5.79	4.78	6.43	3.76	2.97
MPI	2.73	1.52	2.12	2.52	0.94	0.69	1.58	4.23	4.94	7.00	4.47	2.84
MRI	1.73	1.81	1.99	1.88	1.31	1.17	2.00	1.48	1.57	1.27	1.18	1.47
TAI	1.85	1.80	1.80	1.94	1.09	0.58	1.40	2.09	1.19	1.48	1.34	1.89

Tab. 4.7: Variability of climate models for regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.) [%]

climate model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CMCC	14.34	14.91	12.52	13.96	9.29	6.76	8.61	7.96	7.17	5.12	11.75	14.78
EC	8.56	7.02	5.93	7.52	4.49	2.51	4.31	4.86	3.68	5.48	6.42	8.51
GFDL	3.22	3.39	3.02	4.58	2.21	1.56	2.44	3.65	1.70	2.37	2.53	3.55
MPI	2.21	2.17	2.05	2.63	1.33	1.04	1.97	2.77	1.52	2.06	1.70	2.40

Continued on next page

Tab. 4.7: Variability of climate models for regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.) (Continuation)

climate model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
MRI	1.75	1.60	1.72	2.27	1.24	0.73	2.18	2.96	1.59	0.86	0.64	1.84
TAI	2.31	1.85	1.85	1.44	0.90	1.05	1.41	1.96	1.52	2.22	3.44	3.44

Tab. 4.8: Variability of climate models for fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.) [%]

climate model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CMCC	12.53	11.53	10.34	10.91	6.72	5.35	7.30	6.76	6.87	5.65	14.79	15.60
EC	8.77	8.08	6.60	7.75	4.82	3.78	6.48	6.63	4.23	3.28	3.38	6.12
GFDL	4.07	3.13	3.04	2.96	1.13	0.92	3.09	6.13	4.04	5.50	3.88	3.85
MPI	2.45	2.45	2.55	3.08	1.57	0.85	1.72	2.90	1.34	1.58	1.75	2.66
MRI	1.95	2.00	1.74	2.04	1.34	0.98	2.00	1.89	1.86	2.00	1.33	2.19
TAI	3.15	2.08	2.16	1.85	0.80	0.99	1.05	2.30	1.26	1.69	2.97	3.62

4.3.2 Comparison of annual data

As can be seen in figure 4.38 below there are no major differences in the medians of the annual changes in discharges in percent for the various calibration variants for model SSP 245 EC. Usually the calibration variants for the period 1996–2005 have smaller decreases in discharge, and the variants for period 1986–1995 have a little bit bigger decreases in discharge compared to each other. However, the differences are insignificant, often being smaller than 5 %. This is the case for all the used models. For further information see the attachments in chapter 6.4.2. The only real difference is the location on the y-axis. The predictions for CMCC and SSP 126 are the only ones indicating a possible increase of discharges, however small. All the predictions for SSP 126 as well as SSP 245 for CMCC lead to medians around 0 %, while CMCC paired with SSPs 370 and 585 lead to a median around -20 % in discharge. The other predictions all indicate a significant decrease with medians between approximately -55 and -85 %.

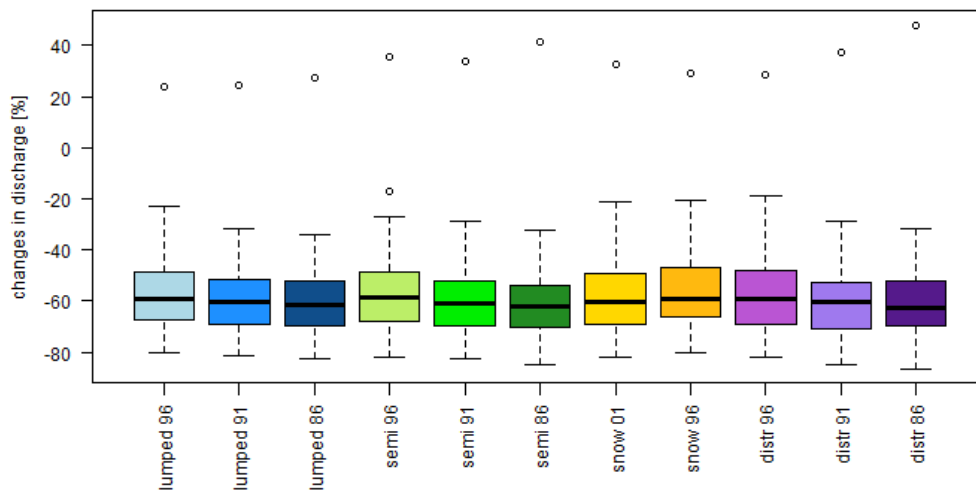


Fig. 4.38: Distribution of annual runoff changes for a 30 year period estimated from the EC climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by different calibration variants labeled as lumped, semi, snow and distr for the different calibration periods. Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 19–49.

Chapter 5

Discussion and conclusion

5.1 Model efficiency of different calibration variants

Generally, all calibration variants lead to satisfying results. The monthly efficiency is significantly better than the daily efficiency, but that is to be expected because the calibration uses monthly data, and thus struggles to recognise daily patterns. Moreover, for the monthly data information about the water usage was available. The inclusion of this information may also be a cause for the better monthly efficiency.

The GOF values for the calibration periods show better results than for the validation period, however, this is also understandable since the model is trained for the calibration periods. Furthermore, a good performance in the calibration period often leads to a good performance in the validation period, because a good efficiency in the calibration period means the model is trained for the given patterns.

No patterns can be discerned about the influence of the calibration period on the GOF for calibration and validation. There is no period that tends to consistently lead to worse results for all models and GOF values. Moreover, there are also no consistent spatial patterns for the different GOF values throughout the catchment.

The model performing the best overall is the distributed model. This goes against the findings in studies performed by Reed et al. (2004) and Pokhrel and Gupta (2011), which both show a better performance for the lumped model. However, both studies reach the conclusion that depending on different conditions other distributed models can perform better than theirs.

The best performance being by the distributed model can be due to the parameters being calculated only for the new zones in each catchment further down the river. Therefore, the real live behaviours are included more precisely.

While the snow model also leads to good efficiencies, especially for the SCAErr, it does show similar GOF values as the semi-distributed model, while needing far more input data and computational time. This is in accordance with Parajka et al. (2007) and Parajka and Blöschl (2008), which show similar results for the conventional single objective approach and the multiple objective calibration. However, while for Parajka et al. (2007) the snow model performed slightly poorer in terms of runoff and for Parajka and Blöschl (2008) the snow model performed slightly better, in this thesis which model performs better is depending on calibration period and GOF value. Slezciak et al. (2017) and Udnæs et al. (2007) claim that the snow data only leads to a better performance for the simulation of the snow, but do not significantly influence other simulations. However, although this thesis shows a much better SCAErr for the snow model in the calibration periods, the SCAErr for the validation period is similar to the semi-distributed model.

The lumped model overall leads to the worst efficiencies out of the four chosen models, however the general performance is still satisfactory. This is in accordance with the findings of Garavaglia et al. (2017), but goes against the findings of de Lavenne et al. (2016). The obtained efficiencies are due to the fact that the subcatchments are not further split into zones and only one data set

for precipitation and air temperature is used. There may be applications for this model when not much computational resources or time are available.

The best performance was obtained for the distributed model calibration in the period 1991–2000.

As for the different calibration parameters the lumped, semi-distributed and snow models often lead to similar behaviour for the same calibration period, while the distributed model does not have the same patterns. This difference in behaviour can be explained by the parameters for the zones for the distributed models staying the same for catchments further down the river, while for the other three models all parameters change for every subcatchment.

Same as with the GOF values the parameters show no universal spatial patterns throughout the catchment.

5.2 Hydrological projections

For the hydrological projections for calibration with the distributed model in the period 1991–2000, the variant with the best fit, the analysis shows that almost all shared socioeconomic pathways result in similar runoff projections. The difference is the green society pathway (SSP 126) for which climate models other than the CMCC indicate a possible increase in discharge and the changes in discharge show a different pattern. This may be because the green society pathway is the only pathway which leads to less inequality and a more sustainable way of live. The other three all lead to more inequality and damages to the environment to varying degrees.

The CMCC model generally leads to the least changes for the discharges. The green society pathway is the pathway with the smallest changes of discharges.

Now a comparison with the findings of other studies can be made.

For the Interreg study a Mann-Kendall test was carried out in the R environment to evaluate trends in runoff characteristics as well as in climate characteristics. A 5 % level was chosen for the assessment of the statistical significance of trends. The notable trends are assessed with regards to the slope of change in the years from 1971–2019. (Parajka et al., 2023b)

The trend for the annual runoff characteristic for the Interreg study shows that in some northern gauging stations in the Svitava and Svatka basins there is a statistically significant decrease of between 10 and 20 mm/10yr, the Svitavy river being the subcatchment of the Thaya with the highest water use. The months with the biggest decline in the monthly runoff are the months April to July, with the largest decrease of about 1 to 5 mm/10yr being in April. That shows that the reduced annual runoff is to a great degree caused by the decrease of runoff during spring and summer. (Parajka et al., 2023b)

A trend for a reduction of the low flows can be seen at different stations in several basins, most of all in the lower Svitavy river basin. However, there are also two stations where a small surge was recorded. (Parajka et al., 2023b)

These findings can be compared to the simulations done for this thesis. There is also a decline for most of the climate models for the annual discharge. The highest declines in discharge for seasonal data usually occur from April to June, the biggest decrease often being in April or June. This also leads to the conclusion that the change in annual runoff is largely due to less runoff during spring and summer. This may be because of less rain in spring and summer or less snow during winter, leading to less snow melt. The fact that precipitation during winter is often in form of snow also explains the often times smaller changes in discharge during winter. Even if there is less snow fall, it still needs to melt to count as runoff.

Blöschl, Schöner, et al. (2011) however claim that for the period 2021–2050 there will be an increase in precipitation in the parts of Austria north of the Alps and a 20 % increase in runoff for

all of Austria besides the southern parts during the winter compared to period 1976–2007. This is not in accordance with the simulations made in this thesis, which predict a decrease in discharge for most of the climate models and shared socioeconomic pathways. While according to Blöschl, Schöner, et al. (2011) the evaporation will increase, it is not likely that the evaporation in winter is enough to lead to a decrease in discharge, while the precipitation increases. Furthermore, due to a projected increase in temperature of approximately 1 °C according to Blöschl, Schöner, et al. (2011) snow would be less likely, so the trend for precipitation would be towards consisting of more rain, leading to more immediate runoff.

For the precipitation in summer Blöschl, Schöner, et al. (2011) prognoses a probable decrease, which is in accordance with the projected decreases in discharge in this thesis.

Blöschl, Schöner, et al. (2011) further claim that while there will be a higher sensitivity to water infrastructure and an increase in water demand, the increase in precipitation is enough to guarantee that the future needs are met. However, if this is not the case, which seems likely with the findings of this thesis, it is important to think about which usages take priority in times of droughts. This can be done on basis of knowledge gained during the summer of 2003. (Blöschl, Schöner, et al., 2011)

Similar findings are seen in Neunteufel et al. (2019), who claim that the northern regions of Austria which contain part of the Thaya basin will observe an increased water demand because of an increase in population and the higher water demand per person. This in combination with the projected decrease in precipitation leads to a very probable need for water imports. (Neunteufel et al., 2019)

Blöschl, Viglione, et al. (2011) also predicts either a slight increase of a decrease in low flow discharges for the northern parts of Austria, which are part of the Thaya basin. This is in accordance with the findings of this thesis.

To help understand the meaning of the trends in runoff and low flows an understanding of trends in climate characteristics is needed. The annual precipitation is raised by approximately 15-30 mm/10yr in 22 % of stations according to the Interreg study. They are mostly located in the North-West and South-East. However, when analysing the changes in the monthly precipitation, there are neither consistent patterns nor changes in the monthly precipitation concerning the quantity according to the Interreg study. (Parajka et al., 2023b)

When looking at the trends of air temperature according to Parajka et al. (2023b) it can be seen that there is an increase at almost all Czech climate stations in the Thaya basin according to the Interreg study. The trend is less significant in Austria because of the shorter data sets. The warming rate for the examined catchment is from 0.2 to 0.8 °C/10yr, while the mean warming rate is 0.4 °C/10yr. The warming rate is the highest in April, from June to August and in November. (Parajka et al., 2023b)

While humidity and wind speed lessen, there is a trend towards a growing sunshine duration. Once again, the trends in the climate data are more prominent in the Czech Republic than in the Austrian part of the Thaya catchment because of the data length of the gauging station according to the Interreg study. (Parajka et al., 2023b)

A water balance screening also has been performed for the Interreg study. The trends for mean annual basin precipitation, water balance evapotranspiration and diagnostic plots of annual runoff, precipitation and evapotranspiration have been examined. There was only a noteworthy increase in two basins in the east and west of the Thaya basin respectively with an increase of the mean annual basin precipitation by approximately 20 mm/10yr. There is however an increase in the evapotranspiration at several gauging stations with an approximate increase of about 19 mm/10yr. (Parajka et al., 2023b)

So the declines in discharges throughout the catchment despite the increase in precipitation can be explained by the higher evapotranspiration as well as the water use.

5.3 Uncertainty of hydrological projections

Since the variabilities for seasonal changes in discharge for the different climate models are overall smaller than for the various calibration variants it can be said that the uncertainty due to the climate models is generally smaller than for the calibration variants. This means that the pick of calibration variant may influence the findings of a study more than the selection of a climate model. This is in disagreement with findings from Parajka et al. (2016), where the calibration depending on the objective function leads to very small uncertainties compared to the different climate scenarios. Lemaitre-Basset et al. (2021) also claim that the climate models are a big source of uncertainties in general. The results of this thesis however seem to complement different results of Parajka et al. (2016) who show that the uncertainty from the calibration period is similar to the uncertainty from the objective function. Lemaitre-Basset et al. (2021) on the other hand show that the different calibration periods lead to different parameter sets. The significance of the resulting uncertainties is different for every hydrological model, but has a higher importance for low-flow because of the slower processes, so the calibration period seems to contribute indirectly to the uncertainties.

The calibration variant with the best fit, the distributed model for period 1991–2000, only leads to the smallest variability for SSP 370, but it still leads to one of the smaller variabilities for the other SSPs. This may be the case because the effectiveness of the calibration variants was generally good.

There are no definitive findings which SSP pathway leads to the biggest uncertainties for the seasonal discharges. However, Lemaitre-Basset et al. (2021) conclude that the representative concentration pathways lead to major uncertainties towards 2100. In this thesis, projections for 2030 are used.

The month with the smallest uncertainties regarding the change in discharge is June, as it has the smallest variability. The highest uncertainty is often during the winter months, in April or August or during autumn. However, it is not possible to discern a pattern. While June often tends to have a high decrease of discharges, and often times the months with high variability have a smaller decrease or an increase, sometimes also months with higher decreases lead to a high variability, so a connection between a high decrease in discharge and a small uncertainty cannot be formed.

Comparing this with Parajka et al. (2016) who show that the uncertainties during summer are smaller for calibration decade and different objective functions compared to winter, but bigger for the climate scenarios it can be seen that not all findings are shared.

As for the annual changes in discharge it is evident that the different calibration variants do not lead to significant differences for the various SSPs and climate models. So, the uncertainties for the annual changes are approximately the same for all SSPs and climate models.

To gain further knowledge about the different uncertainties and changes in discharges a comparison for projections for the year 2100 could be made. This may result in more prominent differences for the SSPs, which could be applied to the planning of the future water resource management.

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Chapter 6

Attachment

6.1 Information about discharge measuring stations

Tab. 6.1: Location and area of discharge measuring stations

Name	ID	Country	LON [°]	LAT [°]	Area [km ²]
Domanín	4440	CZ	16.205154	49.542855	21.41
Rožná	4451	CZ	16.243630	49.475612	57.19
Skryje	4460	CZ	16.317722	49.379354	222.01
Dolní Loučky	4470	CZ	16.359530	49.356910	385.65
Skalní Mlýn	4560	CZ	16.720922	49.369544	154.17
Josefov	4566	CZ	16.679669	49.306362	66.03
Želešice	4580	CZ	16.582301	49.114323	181.52
Rychmanov	4610	CZ	16.763252	49.103832	496.42
Batelov	4630	CZ	15.406206	49.313802	73.48
VD Hubenov	4660	CZ	15.492265	49.392058	19.77
Dolní Bory	4700	CZ	15.985562	49.422529	210.21
Baliny	4720	CZ	15.960383	49.338755	166.50
Příštpo	4760	CZ	15.938986	49.070401	262.51
Janov	4290	CZ	15.434738	48.993028	517.96
Podhradí nad Dyjí	4300	CZ	15.691373	48.903325	1755.48
Vysočany	4320	CZ	15.683321	48.959680	368.71
VD Znojmo	4350	CZ	16.042832	48.853971	2500.28
Trávní Dvůr	4370	CZ	16.437539	48.790911	3535.06
Výrovce	4390	CZ	16.111299	48.928915	382.04
Borovnice	4410	CZ	16.191069	49.678021	127.97
Dalečín	4420	CZ	16.245095	49.595102	366.94
Veverská Bítýška	4480	CZ	16.439670	49.277413	1479.76
Rozhraní	4520	CZ	16.531439	49.600375	227.10
VD Letovice	4530	CZ	16.558696	49.553455	126.59
Letovice	4540	CZ	16.580695	49.532014	423.78
VD Boskovice	4550	CZ	16.698472	49.494014	56.13
Bílovice nad Svitavou	4570	CZ	16.675008	49.245396	1119.98
Židlochovice	4620	CZ	16.616069	49.036317	3938.12
Dvorce	4650	CZ	15.502601	49.382223	307.35
Třebíč-Ptáčov	4690	CZ	15.934770	49.215154	962.71
VD Mostiště	4710	CZ	16.012517	49.392726	222.51
Oslavany	4740	CZ	16.343650	49.115938	861.86
Moravský Krumlov	4770	CZ	16.305678	49.051020	562.26
Ivančice	4780	CZ	16.411736	49.083979	2679.98
Kyjov	4860	CZ	17.121205	49.010572	117.49
Nesměř	4730	CZ	16.025586	49.319626	478.83
Božice	4400	CZ	16.284695	48.839886	643.79
Alt-Prerau	208645	AT	16.463611	48.805000	3587.00
Hardegg	209171	AT	15.867222	48.853056	2382.30

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Tab. 6.1: Location and area of discharge measuring stations (Continuation)

Name	ID	Country	LON [°]	LAT [°]	Area [km ²]
Aigen	209759	AT	15.492222	48.814167	114.10
Alberndorf	209601	AT	15.473611	48.877778	621.50
Dobersberg	214460	AT	15.328340	48.913370	597.60
Haugsdorf	209155	AT	16.060556	48.710278	277.00
Merkengersch	209742	AT	15.307500	48.894722	586.80
Peigarten	209734	AT	15.277500	48.890000	154.70
Raabs an der Thaya	208629	AT	15.500278	48.845833	1405.80
Zwingendorf	208637	AT	16.243056	48.720278	371.50
Pulkau	209510	AT	15.853333	48.706944	87.60
Pulkau	209320	AT	15.853889	48.704722	88.00
Schwarzenau (Süd)	208611	AT	15.259167	48.741944	175.50
Thaua	214437	AT	15.331667	48.718889	78.70
Windigsteig	209775	AT	15.285556	48.765833	107.10

6.2 Efficiency of model calibration

6.2.1 Goodness of fit values

Tab. 6.2: Monthly model efficiencies for calibration and validation for variant lumped 96

ID	NSE cal [-]	logNSE cal [-]	PBIAS cal [%]	KGE cal [-]	SCAErr cal [%]	NSE val [-]	logNSE val [-]	PBIAS val [%]	KGE val [-]	SCAErr val [%]
4440	0.78	0.80	2.10	0.87	4.10	0.67	0.60	-3.60	0.76	3.72
4451	0.85	0.79	3.50	0.91	3.35	0.69	0.69	12.00	0.74	2.43
4460	0.89	0.84	-2.00	0.94	4.55	0.73	0.75	3.80	0.84	6.42
4470	0.85	0.79	4.10	0.90	3.39	0.64	0.66	17.90	0.74	5.54
4560	0.96	0.90	-1.50	0.95	2.08	0.84	0.83	0.50	0.91	1.29
4566	0.78	0.64	2.00	0.80	2.11	0.82	0.58	3.80	0.81	1.40
4580	0.82	0.64	-0.40	0.87	1.22	0.68	0.48	-17.60	0.77	1.89
4610	0.77	0.55	-5.60	0.84	3.05	0.47	0.30	-3.20	0.72	0.61
4630	0.90	0.83	0.20	0.94	2.34	0.79	0.62	6.70	0.88	1.59
4660	0.50	0.48	10.50	0.73	1.52	0.09	-0.67	-48.50	0.29	6.35
4700	0.90	0.69	-1.40	0.94	1.79	0.64	0.45	-0.60	0.82	2.57
4720	0.91	0.82	2.90	0.94	2.96	0.73	0.71	12.20	0.81	3.06
4760	0.78	0.74	0.80	0.88	1.04	0.54	0.46	8.10	0.75	2.42
4290	0.89	0.84	4.80	0.90	0.72	0.71	0.51	23.60	0.72	3.71
4300	0.82	0.85	7.20	0.88	0.95	0.75	0.68	15.20	0.81	3.03
4320	0.83	0.85	6.10	0.89	1.60	0.65	0.55	7.80	0.78	1.91
4350	0.80	0.82	4.40	0.89	0.55	0.82	0.70	-1.00	0.87	1.84
4370	0.83	0.82	1.30	0.91	0.88	0.77	0.55	2.60	0.87	2.27
4390	0.76	0.53	-1.50	0.87	1.78	0.66	0.44	3.70	0.65	1.71
4410	0.94	0.90	0.20	0.94	2.68	0.70	0.70	14.40	0.80	5.64
4420	0.95	0.90	-2.20	0.97	2.54	0.75	0.79	4.50	0.81	6.85
4480	0.95	0.87	2.60	0.96	2.63	0.63	0.68	8.80	0.80	5.35
4520	0.86	0.69	-0.40	0.91	4.54	-0.69	-0.64	12.40	0.46	3.73
4530	0.87	0.68	0.00	0.93	4.05	0.69	0.44	20.80	0.75	6.19
4540	0.90	0.79	-0.10	0.94	1.51	0.20	0.17	14.70	0.67	2.38
4550	0.77	0.59	-2.70	0.69	3.70	0.51	0.48	-31.30	0.39	2.93
4570	0.91	0.81	1.60	0.93	2.09	0.73	0.62	1.20	0.84	0.40
4620	0.92	0.84	3.20	0.93	1.87	0.65	0.62	-1.60	0.83	2.94
4650	0.89	0.83	4.00	0.91	1.90	0.69	0.56	16.50	0.78	2.35
4690	0.91	0.86	0.40	0.90	0.85	0.75	0.71	9.70	0.85	1.94
4710	0.91	0.71	-1.40	0.95	1.83	0.59	0.37	-8.10	0.79	1.64
4740	0.91	0.79	3.40	0.92	3.04	0.73	0.58	-7.40	0.85	3.38
4770	0.73	0.68	-4.30	0.85	1.17	0.68	0.45	2.60	0.80	2.33
4780	0.88	0.74	0.20	0.94	1.55	0.72	0.51	0.30	0.83	2.78

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Tab. 6.2: Monthly model efficiencies for calibration and validation for variant lumped 96 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4860	0.89	0.77	1.90	0.89	3.47	0.45	0.44	17.60	0.65	3.12
4730	0.92	0.77	-0.40	0.96	2.35	0.76	0.52	0.20	0.86	2.88
4400	0.82	0.60	-5.20	0.89	2.08	0.74	0.36	-0.20	0.87	1.29
208645	0.88	0.85	4.60	0.91	1.20	0.36	0.46	10.00	0.51	3.08
209171	0.89	0.87	1.40	0.94	3.12	0.88	0.78	-2.80	0.93	4.25
209601	0.91	0.86	2.60	0.94	1.38	0.80	0.67	11.10	0.86	3.41
209742	0.86	0.89	-2.40	0.83	1.94	0.77	0.74	20.80	0.77	1.50
209734	0.80	0.80	1.60	0.80	1.63	0.47	0.29	44.80	0.52	2.71
208629	0.92	0.89	4.90	0.93	1.84	0.80	0.75	17.40	0.79	2.31
208637	0.66	0.63	-0.40	0.82	2.87	0.26	-1.61	-47.20	0.35	1.34
209510	0.51	0.45	-1.40	0.76	1.49	0.36	-0.05	-14.70	0.68	1.17
209320	0.52	0.45	-3.10	0.75	1.67	0.39	0.14	-12.40	0.70	1.50
208611	0.83	0.84	-4.30	0.82	1.53	0.34	0.45	48.60	0.43	1.05

Tab. 6.3: Daily model efficiencies for calibration and validation for variant lumped 96

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]
4440	0.61	0.57	2.70	0.79	0.79	0.56	0.41	-1.60	0.67
4451	0.65	0.64	3.50	0.80	0.80	0.58	0.56	12.00	0.77
4460	0.68	0.64	-2.00	0.80	0.80	0.46	0.51	3.70	0.73
4470	0.68	0.62	4.10	0.83	0.83	0.43	0.48	17.90	0.67
4560	0.67	0.70	-1.70	0.73	0.73	0.59	0.63	0.50	0.75
4566	0.55	0.47	2.00	0.75	0.75	0.43	0.43	3.70	0.59
4580	0.57	0.43	-0.40	0.71	0.71	0.49	0.35	-17.90	0.64
4610	0.41	0.39	-5.40	0.71	0.71	0.05	0.21	-3.10	0.57
4630	0.67	0.64	0.20	0.82	0.82	0.54	0.45	6.90	0.77
4660	-0.35	0.25	10.70	0.39	0.39	0.13	-0.71	-48.70	0.14
4700	0.60	0.53	-1.50	0.79	0.79	0.28	0.34	-0.50	0.66
4720	0.61	0.46	3.00	0.76	0.76	0.42	0.42	12.40	0.69
4760	0.58	0.41	0.90	0.78	0.78	0.18	0.22	8.50	0.60
209601	0.75	0.75	2.50	0.84	0.84	0.68	0.56	11.10	0.80

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Tab. 6.3: Daily model efficiencies for calibration and validation for variant lumped 96 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]
209742	0.62	0.75	-2.60	0.61	0.55	0.57	20.80	0.62
209734	0.64	0.63	1.50	0.73	0.05	0.26	45.10	0.38
208629	0.71	0.78	4.80	0.79	0.65	0.62	17.40	0.74
208637	0.49	0.43	-0.20	0.72	0.25	-0.44	-47.00	0.22
209510	0.10	0.21	-1.30	0.52	0.02	-0.12	-14.60	0.36
209320	0.06	0.19	-2.90	0.51	0.01	-0.01	-12.40	0.41
208611	0.66	0.72	-4.60	0.69	0.30	0.35	48.90	0.41

Tab. 6.4: Monthly model efficiencies for calibration and validation for variant lumped 91

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4440	0.77	0.71	2.50	0.85	-	0.67	0.62	-3.30	0.75	2.35
4451	0.87	0.81	-3.90	0.91	-	0.71	0.61	5.00	0.85	4.41
4460	0.88	0.85	-0.40	0.94	-	0.76	0.76	8.10	0.85	5.47
4470	0.88	0.81	-2.30	0.90	-	0.69	0.68	6.50	0.83	4.75
4560	0.92	0.92	-1.60	0.95	-	0.83	0.81	-3.50	0.90	2.76
4566	0.85	0.71	-4.20	0.82	-	0.81	0.60	-2.00	0.80	1.29
4580	0.81	0.63	-2.40	0.90	-	0.65	0.23	-26.40	0.69	1.83
4610	0.86	0.74	0.60	0.93	-	0.07	0.35	3.00	0.43	0.46
4630	0.88	0.79	-1.30	0.92	-	0.78	0.66	6.00	0.85	3.68
4660	0.62	0.59	-8.60	0.71	-	0.01	-0.59	-39.50	0.39	3.12
4700	0.88	0.72	-4.70	0.89	-	0.70	0.50	-0.40	0.84	3.57
4720	0.87	0.84	2.00	0.92	-	0.83	0.80	2.90	0.91	3.23
4760	0.84	0.68	-1.30	0.92	-	0.61	0.44	-6.70	0.80	2.17
4290	0.89	0.80	5.60	0.91	-	0.74	0.52	20.60	0.74	3.24
4300	0.87	0.80	3.60	0.92	-	0.83	0.72	4.20	0.87	3.47
4320	0.83	0.70	-1.40	0.91	-	0.61	0.60	-15.60	0.65	2.15
4350	0.87	0.78	1.30	0.92	-	0.80	0.74	-11.00	0.82	2.56
4370	0.89	0.71	0.90	0.93	-	0.78	0.59	-9.50	0.86	2.83
4390	0.84	0.51	-5.30	0.89	-	0.62	0.37	-17.60	0.60	1.52
4410	0.94	0.90	-2.80	0.92	-	0.75	0.71	5.70	0.82	5.40

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Tab. 6.4: Monthly model efficiencies for calibration and validation for variant lumped 91 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4420	0.96	0.91	-2.60	0.97	-	0.78	0.78	-2.40	0.82	5.01
4480	0.96	0.88	3.80	0.94	-	0.67	0.65	8.40	0.82	5.80
4520	0.92	0.83	-0.90	0.91	-	-0.23	-0.69	-3.40	0.48	4.80
4530	0.86	0.56	-4.00	0.82	-	0.39	0.09	3.00	0.41	3.96
4540	0.93	0.83	-0.70	0.96	-	0.44	0.30	6.70	0.69	2.25
4550	0.79	0.66	-11.50	0.70	-	0.45	0.38	-41.30	0.34	1.94
4570	0.93	0.85	3.00	0.95	-	0.72	0.65	-2.70	0.83	1.50
4620	0.93	0.87	0.70	0.94	-	0.62	0.59	-6.70	0.79	4.52
4650	0.87	0.79	0.80	0.93	-	0.73	0.60	9.70	0.83	3.44
4690	0.90	0.84	3.30	0.94	-	0.79	0.75	8.30	0.84	2.50
4710	0.87	0.71	-3.50	0.90	-	0.62	0.39	-10.50	0.78	4.29
4740	0.91	0.81	-0.50	0.95	-	0.72	0.58	-11.90	0.80	3.82
4770	0.83	0.65	-3.00	0.91	-	0.59	0.45	-4.30	0.76	2.40
4780	0.91	0.79	-1.90	0.93	-	0.66	0.41	-7.30	0.74	4.25
4860	0.89	0.82	-0.30	0.86	-	0.42	0.35	20.30	0.63	3.39
4730	0.90	0.78	0.20	0.95	-	0.76	0.50	-1.50	0.88	2.71
4400	0.89	0.56	-2.80	0.90	-	0.68	0.02	-19.80	0.74	1.23
208645	0.90	0.71	-2.90	0.94	-	0.60	0.36	-9.40	0.74	3.72
209171	0.91	0.82	-0.10	0.95	-	0.85	0.77	-7.00	0.88	4.46
209601	0.90	0.82	1.60	0.94	-	0.84	0.65	-1.00	0.87	3.12
208629	0.92	0.85	0.00	0.95	-	0.89	0.79	1.40	0.93	5.50
208637	0.84	0.63	0.70	0.92	-	0.40	-1.13	-43.60	0.41	1.18
209510	0.83	0.55	-4.50	0.89	-	0.22	-0.12	-13.00	0.57	1.29
209320	0.85	0.55	-2.00	0.92	-	0.31	-0.29	-13.00	0.63	1.22
208611	0.75	0.77	-8.30	0.78	-	0.52	0.53	48.00	0.47	5.91

Tab. 6.5: Daily model efficiencies for calibration and validation for variant lumped 91

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]
4440	0.63	0.60	2.50	0.81	0.81	0.58	0.49	-1.10	0.70
4451	0.68	0.60	-3.80	0.78	0.78	0.52	0.42	5.00	0.73

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Tab. 6.5: Daily model efficiencies for calibration and validation for variant lumped 91 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	NSE val	logNSE val	PBIAS val	KGE val	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]
4460	0.73	0.74	-0.50	0.83	0.57	0.63	8.00	0.75	0.57	0.63	8.00	0.75
4470	0.70	0.57	-2.40	0.85	0.42	0.45	6.50	0.69	0.42	0.45	6.50	0.69
4560	0.66	0.72	-1.70	0.76	0.57	0.59	-3.40	0.71	0.57	0.59	-3.40	0.71
4566	0.34	0.50	-4.20	0.68	0.36	0.46	-2.10	0.57	0.36	0.46	-2.10	0.57
4580	0.61	0.42	-2.30	0.81	0.41	0.21	-26.90	0.58	0.41	0.21	-26.90	0.58
4610	0.62	0.45	0.70	0.81	0.07	0.25	3.10	0.55	0.07	0.25	3.10	0.55
4630	0.75	0.67	-1.30	0.85	0.60	0.49	6.30	0.72	0.60	0.49	6.30	0.72
4660	0.39	0.41	-8.40	0.56	0.11	-0.61	-39.80	0.21	0.11	-0.61	-39.80	0.21
4700	0.74	0.60	-4.70	0.82	0.49	0.37	-0.10	0.71	0.49	0.37	-0.10	0.71
4720	0.63	0.61	1.90	0.74	0.54	0.58	3.00	0.70	0.54	0.58	3.00	0.70
4760	0.69	0.54	-1.20	0.81	0.41	0.27	-6.40	0.71	0.41	0.27	-6.40	0.71
209601	0.74	0.62	1.60	0.86	0.70	0.48	-1.00	0.77	0.70	0.48	-1.00	0.77
208629	0.75	0.62	-0.10	0.83	0.69	0.56	1.40	0.79	0.69	0.56	1.40	0.79
208637	0.55	0.32	1.50	0.77	0.24	-0.35	-43.40	0.35	0.24	-0.35	-43.40	0.35
209510	0.72	0.37	-4.50	0.85	0.10	-0.09	-13.00	0.57	0.10	-0.09	-13.00	0.57
209320	0.69	0.37	-1.90	0.82	0.25	-0.14	-12.90	0.60	0.25	-0.14	-12.90	0.60
208611	0.58	0.65	-8.50	0.61	0.44	0.37	48.10	0.44	0.44	0.37	48.10	0.44

Tab. 6.6: Monthly model efficiencies for calibration and validation for variant lumped 86

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4440	0.88	0.83	-2.40	0.93	-	0.76	0.65	7.40	0.86	2.08
4451	0.82	0.80	1.20	0.86	-	0.42	0.49	36.50	0.50	2.35
4460	0.88	0.85	2.60	0.93	-	0.74	0.76	15.20	0.76	2.86
4470	0.88	0.82	-1.00	0.93	-	0.68	0.66	13.60	0.79	3.15
4560	0.87	0.90	-1.60	0.87	-	0.79	0.81	-2.60	0.89	1.25
4566	0.81	0.68	0.60	0.85	-	0.79	0.53	4.90	0.82	1.07
4580	0.79	0.64	-8.10	0.85	-	0.42	0.39	-16.70	0.68	2.12
4610	0.81	0.75	-1.80	0.90	-	0.23	0.41	5.90	0.49	0.62
4630	0.88	0.82	0.40	0.92	-	0.65	0.64	1.20	0.83	4.69
4660	0.50	0.48	-3.50	0.68	-	0.14	-0.23	-36.10	0.41	5.48

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Tab. 6.6: Monthly model efficiencies for calibration and validation for variant lumped 86 (Continuation)

ID	NSE cal [-]	logNSE cal [-]	PBIAS cal [%]	KGE cal [-]	SCAErr cal [%]	NSE val [-]	logNSE val [-]	PBIAS val [%]	KGE val [-]	SCAErr val [%]
4700	0.81	0.67	-3.10	0.83	-	0.70	0.48	1.00	0.85	2.10
4720	0.89	0.86	-1.80	0.92	-	0.83	0.80	-0.70	0.91	3.65
4760	0.77	0.54	-7.90	0.84	-	0.26	0.38	-3.80	0.65	3.51
4290	0.88	0.81	1.90	0.92	-	0.69	0.59	23.90	0.64	3.42
4300	0.88	0.80	1.10	0.92	-	0.84	0.74	12.80	0.85	3.61
4320	0.88	0.69	-1.00	0.94	-	0.50	0.59	-11.10	0.69	2.28
4350	0.86	0.72	0.90	0.93	-	0.80	0.77	6.00	0.87	2.19
4370	0.85	0.60	-4.30	0.91	-	0.74	0.56	0.50	0.84	2.27
4390	0.85	0.46	-6.90	0.89	-	0.44	0.43	-22.90	0.47	1.76
4410	0.90	0.90	-0.60	0.92	-	0.78	0.72	10.60	0.84	4.60
4420	0.91	0.89	-1.10	0.94	-	0.79	0.78	-0.40	0.82	4.91
4480	0.90	0.87	4.00	0.89	-	0.57	0.73	14.00	0.64	3.02
4520	0.68	0.67	1.70	0.84	-	-1.28	-1.15	16.20	0.35	0.58
4530	0.67	0.42	-2.80	0.75	-	0.30	0.02	0.70	0.32	3.43
4540	0.79	0.75	0.20	0.88	-	0.36	0.19	11.10	0.72	1.55
4550	0.60	0.56	-7.60	0.68	-	0.62	0.57	-30.10	0.50	1.77
4570	0.84	0.80	-0.50	0.91	-	0.73	0.54	-3.10	0.86	0.98
4620	0.86	0.81	2.80	0.91	-	0.61	0.59	-2.00	0.77	2.94
4650	0.88	0.80	-1.40	0.94	-	0.73	0.58	2.90	0.86	4.17
4690	0.90	0.84	4.80	0.93	-	0.81	0.69	1.30	0.88	2.62
4710	0.83	0.64	-3.70	0.88	-	0.67	0.39	-10.60	0.79	4.31
4740	0.87	0.74	4.20	0.92	-	0.72	0.59	-5.10	0.85	2.47
4770	0.80	0.50	-8.10	0.86	-	0.19	0.38	5.50	0.54	1.72
4780	0.88	0.75	-3.00	0.90	-	0.67	0.46	-7.60	0.77	2.16
4860	0.79	0.75	2.70	0.85	-	0.27	0.40	22.70	0.55	3.59
4730	0.88	0.75	-1.10	0.92	-	0.81	0.45	-4.00	0.88	2.04
4400	0.87	0.44	-9.60	0.88	-	0.38	0.13	-14.50	0.64	1.91
208645	0.84	0.55	-1.20	0.92	-	0.55	0.44	2.60	0.69	3.29
209171	0.90	0.77	-0.40	0.95	-	0.82	0.78	-0.50	0.87	4.52
208629	0.91	0.83	-3.80	0.87	-	0.86	0.76	2.70	0.92	6.27
208637	0.68	0.42	-3.40	0.82	-	0.18	-1.16	-43.50	0.29	1.66
209510	0.62	0.44	-6.90	0.80	-	0.32	0.13	-3.30	0.63	1.32
209320	0.63	0.41	-1.00	0.82	-	0.24	0.06	3.20	0.60	0.87
208611	0.76	0.78	-6.50	0.74	-	0.48	0.40	50.40	0.46	7.42

Tab. 6.7: Daily model efficiencies for calibration and validation for variant lumped 86

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	NSE val	logNSE val	PBIAS val	KGE val	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]
4440	0.78	0.68	-2.40	0.82	0.66	0.50	7.80	0.78	0.66	0.50	7.80	0.78
4451	0.71	0.61	1.30	0.79	0.41	0.37	36.60	0.55	0.41	0.37	36.60	0.55
4460	0.76	0.73	2.50	0.83	0.60	0.65	15.10	0.76	0.60	0.65	15.10	0.76
4470	0.77	0.67	-1.10	0.85	0.50	0.54	13.60	0.72	0.50	0.54	13.60	0.72
4560	0.68	0.70	-1.60	0.79	0.56	0.64	-2.50	0.74	0.56	0.64	-2.50	0.74
4566	0.51	0.51	0.70	0.72	0.37	0.40	4.90	0.57	0.37	0.40	4.90	0.57
4580	0.66	0.53	-8.00	0.76	0.35	0.33	-17.30	0.63	0.35	0.33	-17.30	0.63
4610	0.49	0.46	-1.70	0.63	0.21	0.29	6.00	0.62	0.21	0.29	6.00	0.62
4630	0.76	0.67	0.30	0.82	0.42	0.47	1.30	0.67	0.42	0.47	1.30	0.67
4660	0.30	0.16	-3.00	0.55	0.01	-0.26	-36.30	0.13	0.01	-0.26	-36.30	0.13
4700	0.73	0.50	-3.10	0.82	0.46	0.31	1.20	0.73	0.46	0.31	1.20	0.73
4720	0.72	0.59	-1.80	0.84	0.52	0.56	-0.50	0.67	0.52	0.56	-0.50	0.67
4760	0.67	0.39	-8.00	0.82	-0.01	0.24	-3.40	0.55	-0.01	0.24	-3.40	0.55
208629	0.73	0.65	-3.90	0.73	0.65	0.57	2.60	0.78	0.65	0.57	2.60	0.78
208637	-0.03	0.16	-2.50	0.42	0.09	-0.32	-43.20	0.11	0.09	-0.32	-43.20	0.11
209510	0.07	0.19	-6.80	0.57	-0.13	-0.04	-3.30	0.47	-0.13	-0.04	-3.30	0.47
209320	0.47	0.19	-0.90	0.73	0.22	-0.01	3.30	0.63	0.22	-0.01	3.30	0.63
208611	0.55	0.61	-6.60	0.66	0.45	0.24	50.80	0.44	0.45	0.24	50.80	0.44

Tab. 6.8: Monthly model efficiencies for calibration and validation for variant semi-distributed 96

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4470	0.87	0.79	-0.90	0.92	4.17	0.72	0.69	9.50	0.83	4.52
4560	0.95	0.89	0.80	0.95	1.53	0.85	0.82	6.30	0.90	1.01
4610	0.75	0.53	-8.10	0.81	3.48	0.55	0.30	-14.20	0.74	0.67
4660	0.48	0.49	7.20	0.73	1.94	0.05	-0.72	-50.10	0.25	8.06
4700	0.83	0.67	0.30	0.81	2.99	0.43	0.45	9.00	0.66	2.28
4720	0.90	0.82	3.90	0.90	3.38	0.72	0.72	14.60	0.77	3.06
4760	0.82	0.73	-7.00	0.89	1.10	0.54	0.44	4.60	0.77	2.47
4290	0.91	0.85	3.80	0.91	0.75	0.77	0.55	12.00	0.83	1.88
4300	0.92	0.89	-0.20	0.94	0.36	0.84	0.73	6.90	0.86	1.58

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Tab. 6.8: Monthly model efficiencies for calibration and validation for variant semi-distributed 96 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4320	0.86	0.85	3.50	0.88	0.18	0.53	0.52	16.10	0.73	1.45
4350	0.90	0.89	0.70	0.95	2.50	0.83	0.76	7.50	0.89	1.56
4370	0.89	0.85	3.30	0.92	1.45	0.79	0.57	8.10	0.87	1.41
4390	0.80	0.57	-3.50	0.89	1.17	0.67	0.37	18.80	0.73	1.03
4420	0.94	0.90	0.90	0.96	2.56	0.74	0.78	5.80	0.85	6.95
4480	0.95	0.87	3.60	0.90	1.30	0.70	0.70	8.50	0.82	2.23
4530	0.87	0.68	-1.00	0.93	8.74	0.74	0.52	5.60	0.79	8.54
4540	0.89	0.79	1.10	0.92	1.33	0.45	0.37	0.60	0.70	0.89
4550	0.77	0.60	2.00	0.70	1.80	0.47	0.50	-30.90	0.35	2.17
4570	0.89	0.80	-2.40	0.92	1.53	0.67	0.64	-8.50	0.76	0.40
4620	0.93	0.84	2.10	0.92	0.36	0.75	0.70	-1.70	0.87	0.58
4650	0.88	0.83	1.00	0.93	1.67	0.73	0.59	11.40	0.81	3.00
4690	0.91	0.87	-0.60	0.94	1.77	0.80	0.75	10.20	0.86	2.39
4710	0.92	0.74	-2.20	0.95	2.65	0.56	0.41	0.30	0.77	3.38
4740	0.93	0.79	-1.90	0.94	1.59	0.75	0.63	-3.00	0.87	1.62
4770	0.76	0.69	-0.50	0.88	0.48	0.53	0.43	5.90	0.74	0.70
4780	0.90	0.73	-1.70	0.94	1.01	0.72	0.53	2.90	0.85	1.35
4730	0.92	0.77	-5.20	0.92	1.75	0.76	0.55	-3.10	0.88	1.78
4400	0.84	0.61	-5.50	0.89	1.43	0.65	0.33	2.60	0.73	1.16
208645	0.89	0.84	0.40	0.94	1.29	0.62	0.50	6.70	0.67	1.16
209171	0.90	0.86	2.40	0.92	1.29	0.89	0.78	-0.50	0.92	1.89
209601	0.91	0.86	3.30	0.93	1.47	0.80	0.67	12.20	0.85	1.75
209742	0.86	0.89	-1.60	0.83	1.70	0.77	0.74	21.50	0.77	1.23
209734	0.79	0.77	2.90	0.80	2.31	0.47	0.29	45.10	0.51	2.75
208629	0.91	0.88	5.80	0.93	0.87	0.80	0.74	18.90	0.77	1.42
208637	0.62	0.61	4.80	0.78	3.05	0.28	-1.38	-45.30	0.38	1.33

Tab. 6.9: Daily model efficiencies for calibration and validation for variant semi-distributed 96

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]
4440	0.61	0.57	0.57	2.70	0.79	0.56	0.41	-1.60	0.67

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Tab. 6.9: Daily model efficiencies for calibration and validation for variant semi-distributed 96 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]
4451	0.65	0.64	3.50	0.80	0.58	0.56	12.00	0.77
4460	0.68	0.64	-2.00	0.80	0.46	0.51	3.70	0.73
4470	0.68	0.63	-1.00	0.83	0.53	0.54	9.50	0.73
4560	0.67	0.73	0.70	0.73	0.60	0.65	6.20	0.75
4566	0.55	0.47	2.00	0.75	0.43	0.43	3.70	0.59
4580	0.57	0.43	-0.40	0.71	0.49	0.35	-17.90	0.64
4610	0.54	0.39	-7.90	0.77	0.33	0.22	-14.10	0.61
4630	0.67	0.64	0.20	0.82	0.54	0.45	6.90	0.77
4660	-0.32	0.27	7.30	0.40	0.12	-0.73	-50.30	0.11
4700	0.51	0.55	0.20	0.67	0.08	0.36	8.90	0.53
4720	0.56	0.49	3.90	0.74	0.44	0.44	14.70	0.69
4760	0.59	0.49	-7.00	0.73	0.24	0.23	5.00	0.64
209601	0.76	0.76	3.20	0.84	0.68	0.56	12.30	0.80
209742	0.62	0.77	-1.80	0.60	0.56	0.58	21.50	0.62
209734	0.66	0.62	2.80	0.72	0.07	0.26	45.40	0.38
208629	0.73	0.78	5.70	0.79	0.66	0.62	18.90	0.74
208637	0.47	0.46	5.00	0.71	0.27	-0.32	-45.10	0.24
209510	0.10	0.21	-1.30	0.52	0.02	-0.12	-14.60	0.36
209320	0.06	0.19	-2.90	0.51	0.01	-0.01	-12.40	0.41
208611	0.66	0.72	-4.60	0.69	0.30	0.35	48.90	0.41

Tab. 6.10: Monthly model efficiencies for calibration and validation for variant semi-distributed 91

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4470	0.91	0.81	-8.30	0.91	-	0.76	0.70	-2.00	0.87	3.73
4560	0.93	0.92	1.70	0.91	-	0.86	0.84	2.50	0.92	1.21
4610	0.84	0.74	-3.80	0.87	-	0.39	0.35	-9.10	0.65	0.49
4660	0.58	0.59	-15.70	0.67	-	-0.06	-0.72	-41.40	0.33	3.98
4700	0.90	0.73	0.20	0.93	-	0.61	0.50	9.20	0.76	2.50
4720	0.93	0.85	-2.80	0.95	-	0.83	0.81	5.80	0.89	3.31
4760	0.80	0.65	-9.40	0.82	-	0.59	0.41	-10.00	0.77	2.63

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Tab. 6.10: Monthly model efficiencies for calibration and validation for variant semi-distributed 91 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4290	0.89	0.82	1.90	0.94	-	0.83	0.57	7.00	0.89	2.40
4300	0.92	0.84	0.60	0.95	-	0.87	0.75	1.20	0.88	2.56
4320	0.86	0.74	1.20	0.93	-	0.66	0.64	1.60	0.82	1.66
4350	0.93	0.81	0.20	0.96	-	0.85	0.75	-6.20	0.85	1.88
4370	0.90	0.71	-3.30	0.93	-	0.83	0.57	-9.10	0.88	1.72
4390	0.89	0.48	-1.90	0.94	-	0.69	0.32	-4.60	0.82	1.04
4420	0.96	0.90	-0.50	0.98	-	0.76	0.76	0.10	0.81	3.76
4480	0.96	0.88	2.70	0.93	-	0.72	0.64	9.00	0.82	1.99
4530	0.86	0.59	-3.00	0.84	-	0.33	0.10	-5.90	0.34	3.83
4540	0.93	0.83	-0.40	0.92	-	0.41	0.21	-5.30	0.58	1.16
4550	0.83	0.70	0.80	0.82	-	0.49	0.47	-37.00	0.36	1.07
4570	0.95	0.87	-0.80	0.95	-	0.70	0.62	-6.50	0.74	0.40
4620	0.94	0.88	3.80	0.92	-	0.71	0.67	-3.40	0.85	1.28
4650	0.89	0.78	1.30	0.94	-	0.76	0.58	9.40	0.83	2.32
4690	0.92	0.83	3.40	0.94	-	0.81	0.72	10.40	0.83	1.63
4710	0.91	0.72	-3.90	0.90	-	0.66	0.42	-4.00	0.82	3.18
4740	0.93	0.82	2.30	0.95	-	0.81	0.63	3.70	0.90	1.13
4770	0.84	0.62	-5.60	0.90	-	0.43	0.40	-8.40	0.72	1.25
4780	0.92	0.81	-0.80	0.92	-	0.66	0.42	0.70	0.76	1.34
4730	0.93	0.81	-0.40	0.96	-	0.74	0.51	4.10	0.86	2.87
4400	0.88	0.56	-3.70	0.93	-	0.71	0.22	-16.80	0.77	0.85
208645	0.89	0.70	-1.40	0.93	-	0.70	0.44	-7.30	0.78	1.17
209171	0.91	0.81	-1.90	0.95	-	0.88	0.75	-7.00	0.90	2.06
209601	0.89	0.82	2.60	0.93	-	0.85	0.66	0.40	0.88	1.77
208629	0.91	0.84	1.10	0.95	-	0.89	0.79	3.00	0.93	2.39
208637	0.82	0.62	4.90	0.89	-	0.42	-0.95	-41.90	0.43	0.79

Tab. 6.11: Daily model efficiencies for calibration and validation for variant semi-distributed 91

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4440	0.63	0.60	0.60	2.50	0.81	0.58	0.49	-1.10	0.70	

Continued on next page

Tab. 6.11: Daily model efficiencies for calibration and validation for variant semi-distributed 91 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]
4451	0.68	0.60	-3.80	0.78	0.52	0.42	5.00	0.73
4460	0.73	0.74	-0.50	0.83	0.57	0.63	8.00	0.75
4470	0.74	0.60	-8.40	0.84	0.54	0.50	-2.00	0.72
4560	0.66	0.74	1.70	0.73	0.58	0.65	2.40	0.72
4566	0.34	0.50	-4.20	0.68	0.36	0.46	-2.10	0.57
4580	0.61	0.42	-2.30	0.81	0.41	0.21	-26.90	0.58
4610	0.65	0.50	-3.80	0.78	0.29	0.27	-9.10	0.66
4630	0.75	0.67	-1.30	0.85	0.60	0.49	6.30	0.72
4660	0.39	0.43	-15.40	0.52	0.08	-0.67	-41.70	0.16
4700	0.76	0.62	0.10	0.88	0.44	0.38	9.30	0.72
4720	0.65	0.63	-2.90	0.74	0.56	0.59	5.90	0.73
4760	0.61	0.53	-9.20	0.68	0.39	0.26	-9.60	0.68
209601	0.74	0.67	2.60	0.85	0.71	0.53	0.40	0.78
208629	0.75	0.67	1.10	0.83	0.70	0.60	3.00	0.80
208637	0.55	0.34	5.70	0.77	0.28	-0.25	-41.80	0.37
209510	0.72	0.37	-4.50	0.85	0.10	-0.09	-13.00	0.57
209320	0.69	0.37	-1.90	0.82	0.25	-0.14	-12.90	0.60
208611	0.58	0.65	-8.50	0.61	0.44	0.37	48.10	0.44

Tab. 6.12: Monthly model efficiencies for calibration and validation for variant semi-distributed 86

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4470	0.91	0.83	-4.30	0.93	-	0.76	0.69	4.90	0.87	2.35
4560	0.88	0.89	-0.30	0.88	-	0.81	0.81	3.50	0.90	1.11
4610	0.81	0.74	-4.40	0.88	-	0.43	0.40	-5.20	0.66	0.88
4660	0.51	0.48	-14.70	0.60	-	0.10	-0.35	-38.50	0.36	5.91
4700	0.84	0.70	-2.80	0.88	-	0.58	0.49	10.20	0.70	2.25
4720	0.88	0.85	-11.00	0.83	-	0.83	0.81	0.50	0.91	3.59
4760	0.75	0.49	-17.70	0.76	-	0.30	0.35	-5.70	0.67	2.50
4290	0.91	0.82	0.60	0.93	-	0.81	0.56	9.90	0.84	2.32
4300	0.91	0.81	-3.00	0.93	-	0.85	0.74	4.30	0.90	2.73

Continued on next page

Tab. 6.12: Monthly model efficiencies for calibration and validation for variant semi-distributed 86 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4320	0.89	0.70	-7.10	0.88	-	0.59	0.60	-0.60	0.77	2.08
4350	0.89	0.73	1.30	0.94	-	0.83	0.75	8.30	0.85	1.76
4370	0.87	0.62	-3.00	0.92	-	0.82	0.59	3.90	0.86	2.39
4390	0.87	0.42	-9.20	0.86	-	0.51	0.39	-2.60	0.74	1.66
4420	0.91	0.89	0.90	0.95	-	0.77	0.77	3.50	0.86	3.17
4480	0.93	0.88	0.70	0.95	-	0.69	0.72	12.00	0.75	1.80
4530	0.68	0.45	-4.60	0.70	-	0.15	0.02	-12.20	0.16	3.40
4540	0.81	0.77	0.70	0.86	-	0.40	0.25	-6.50	0.63	1.54
4550	0.64	0.60	-6.10	0.75	-	0.57	0.58	-34.90	0.42	1.74
4570	0.85	0.81	0.20	0.92	-	0.73	0.65	-3.60	0.86	0.40
4620	0.88	0.84	3.00	0.93	-	0.76	0.68	-0.60	0.86	1.50
4650	0.85	0.80	-2.40	0.88	-	0.76	0.64	3.50	0.87	4.11
4690	0.91	0.85	-2.30	0.90	-	0.82	0.69	-0.10	0.89	2.08
4710	0.85	0.68	-5.00	0.86	-	0.67	0.40	-0.60	0.84	2.30
4740	0.91	0.76	0.30	0.93	-	0.74	0.60	4.20	0.86	1.28
4770	0.80	0.47	-8.50	0.85	-	0.27	0.35	4.80	0.64	1.40
4780	0.90	0.78	-1.70	0.91	-	0.66	0.48	-1.10	0.81	1.20
4730	0.90	0.77	-2.70	0.93	-	0.72	0.51	3.90	0.85	2.26
4400	0.88	0.46	-8.30	0.87	-	0.42	0.24	-8.30	0.70	1.11
208645	0.84	0.56	-4.20	0.91	-	0.65	0.46	-0.70	0.75	1.95
209171	0.91	0.76	-0.90	0.94	-	0.88	0.74	3.30	0.85	1.90
208629	0.91	0.83	-2.90	0.87	-	0.86	0.77	4.30	0.92	3.03
208637	0.64	0.41	3.00	0.82	-	0.21	-0.98	-41.40	0.32	1.79

Tab. 6.13: Daily model efficiencies for calibration and validation for variant semi-distributed 86

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]
4440	0.78	0.68	-2.40	0.82	-	0.66	0.50	7.80	0.78
4451	0.71	0.61	1.30	0.79	-	0.41	0.37	36.60	0.55
4460	0.76	0.73	2.50	0.83	-	0.60	0.65	15.10	0.76
4470	0.80	0.69	-4.40	0.85	-	0.59	0.56	4.90	0.76

Continued on next page

Tab. 6.13: Daily model efficiencies for calibration and validation for variant semi-distributed 86 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]
4560	0.69	0.72	-0.30	0.79	0.59	0.67	3.50	0.75
4566	0.51	0.51	0.70	0.72	0.37	0.40	4.90	0.57
4580	0.66	0.53	-8.00	0.76	0.35	0.33	-17.30	0.63
4610	0.50	0.50	-4.30	0.62	0.36	0.30	-5.10	0.69
4630	0.76	0.67	0.30	0.82	0.42	0.47	1.30	0.67
4660	0.34	0.18	-14.30	0.47	0.00	-0.33	-38.80	0.08
4700	0.76	0.56	-2.80	0.85	0.38	0.33	10.30	0.67
4720	0.72	0.58	-10.90	0.76	0.53	0.57	0.60	0.69
4760	0.71	0.37	-17.80	0.77	0.13	0.22	-5.30	0.60
208629	0.75	0.68	-3.00	0.74	0.67	0.60	4.20	0.79
208637	-0.23	0.15	3.90	0.42	0.12	-0.24	-41.10	0.15
209510	0.07	0.19	-6.80	0.57	-0.13	-0.04	-3.30	0.47
209320	0.47	0.19	-0.90	0.73	0.22	-0.01	3.30	0.63
208611	0.55	0.61	-6.60	0.66	0.45	0.24	50.80	0.44

Tab. 6.14: Monthly model efficiencies for calibration and validation for variant snow 01-11

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4440	0.87	0.78	-0.20	0.91	2.96	0.67	0.55	12.90	0.77	5.88
4451	0.86	0.77	1.20	0.91	2.15	0.74	0.62	15.50	0.77	5.23
4460	0.93	0.84	0.90	0.96	2.47	0.74	0.72	9.60	0.81	5.74
4470	0.88	0.78	6.30	0.87	1.75	0.66	0.67	17.90	0.70	4.49
4560	0.95	0.88	-1.00	0.96	0.79	0.86	0.84	3.60	0.92	1.17
4566	0.85	0.72	-2.50	0.90	2.18	0.67	0.59	-2.80	0.64	1.09
4580	0.77	0.71	-1.80	0.88	0.94	0.68	0.48	-7.60	0.83	0.67
4610	0.79	0.63	-3.50	0.89	0.95	0.48	0.33	-17.70	0.71	0.64
4630	0.91	0.85	1.80	0.95	1.38	0.72	0.64	7.90	0.84	2.68
4660	0.56	0.52	2.30	0.76	2.38	0.06	-0.59	-48.10	0.23	4.43
4700	0.86	0.68	-1.50	0.93	1.58	0.61	0.48	12.50	0.75	3.72
4720	0.91	0.83	0.00	0.95	1.95	0.81	0.78	-0.10	0.87	2.63
4760	0.85	0.78	1.10	0.93	0.76	0.48	0.44	14.70	0.69	1.75

Continued on next page

Tab. 6.14: Monthly model efficiencies for calibration and validation for variant snow 01-11 (Continuation)

ID	NSE cal [-]	logNSE cal [-]	PBIAS cal [%]	KGE cal [-]	SCAErr cal [%]	NSE val [-]	logNSE val [-]	PBIAS val [%]	KGE val [-]	SCAErr val [%]
4290	0.89	0.85	4.60	0.92	0.80	0.80	0.58	11.30	0.83	2.07
4300	0.92	0.88	2.20	0.95	0.49	0.83	0.72	14.70	0.83	1.23
4320	0.83	0.84	2.30	0.90	0.68	0.64	0.51	19.30	0.75	1.52
4350	0.92	0.87	2.70	0.95	0.45	0.77	0.71	17.00	0.79	1.05
4370	0.90	0.82	2.00	0.94	0.42	0.79	0.56	11.20	0.83	1.23
4390	0.82	0.77	0.20	0.89	0.75	0.63	0.26	34.20	0.57	0.82
4410	0.94	0.87	-1.00	0.97	2.71	0.73	0.69	13.20	0.82	5.63
4420	0.95	0.89	0.40	0.98	1.92	0.76	0.75	7.90	0.85	4.23
4480	0.93	0.86	2.10	0.94	0.69	0.68	0.69	10.20	0.78	3.05
4520	0.65	0.58	0.00	0.83	1.55	0.03	-0.11	-2.40	0.51	2.40
4530	0.89	0.84	0.90	0.93	2.09	0.73	0.72	9.10	0.81	4.68
4540	0.85	0.79	0.70	0.93	0.66	0.50	0.40	-1.10	0.70	1.31
4550	0.81	0.70	6.60	0.88	1.83	0.66	0.74	-21.50	0.59	2.47
4570	0.89	0.85	3.70	0.89	0.62	0.74	0.68	-2.50	0.80	0.51
4620	0.91	0.83	0.80	0.91	0.72	0.77	0.62	-6.60	0.87	1.40
4650	0.90	0.83	1.90	0.94	0.81	0.76	0.61	6.40	0.84	2.50
4690	0.93	0.87	3.40	0.95	0.60	0.83	0.71	4.50	0.89	1.46
4710	0.89	0.71	-2.40	0.94	1.57	0.63	0.39	4.80	0.80	3.10
4740	0.91	0.80	2.30	0.95	0.96	0.77	0.63	2.30	0.84	1.23
4770	0.84	0.74	1.20	0.92	0.56	0.57	0.45	7.70	0.71	0.68
4780	0.92	0.83	1.00	0.96	0.46	0.71	0.59	6.70	0.81	0.62
4860	0.93	0.81	-1.50	0.95	0.77	0.69	0.56	3.40	0.84	1.90
4730	0.92	0.75	-0.30	0.96	1.21	0.79	0.54	-1.10	0.88	1.51
4400	0.79	0.68	-2.70	0.89	0.87	0.64	0.32	11.70	0.68	1.16
208645	0.89	0.82	1.80	0.93	0.41	0.52	0.45	17.40	0.58	0.65
209171	0.91	0.87	4.20	0.92	0.56	0.89	0.75	2.80	0.94	1.08
209759	0.89	0.83	3.10	0.94	1.43	0.84	0.66	4.20	0.89	2.92
209601	0.90	0.88	2.80	0.94	0.79	0.84	0.72	8.80	0.87	1.40
209742	0.90	0.89	-0.10	0.91	0.65	0.72	0.69	28.80	0.68	1.58
209734	0.74	0.80	2.60	0.80	0.89	0.69	0.58	25.20	0.72	2.35
208629	0.92	0.88	1.60	0.95	0.60	0.83	0.77	15.10	0.81	1.33
208637	0.70	0.67	-3.20	0.78	1.15	0.25	-1.31	-45.30	0.33	0.86
209510	0.70	0.59	-2.90	0.81	1.35	0.29	-0.64	-22.60	0.65	1.93
209320	0.70	0.58	-1.00	0.81	1.45	0.30	-0.58	-20.40	0.66	1.73
208611	0.86	0.87	-0.60	0.90	1.48	0.46	0.52	47.80	0.46	1.34

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Tab. 6.14: Monthly model efficiencies for calibration and validation for variant snow 01-11 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
209775	0.91	0.83	2.10	0.95	0.86	0.77	0.67	-2.80	0.79	1.51

Tab. 6.15: Daily model efficiencies for calibration and validation for variant snow 01-11

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]
4440	0.54	0.54	0.90	0.78	0.56	0.33	0.33	17.10	0.66
4451	0.70	0.55	1.20	0.79	0.56	0.45	0.45	15.50	0.74
4460	0.72	0.62	0.80	0.76	0.56	0.53	0.53	9.50	0.77
4470	0.72	0.64	6.30	0.85	0.52	0.53	0.53	17.80	0.71
4560	0.70	0.74	-1.10	0.81	0.59	0.71	0.71	3.40	0.74
4566	0.66	0.58	-2.60	0.77	0.32	0.47	0.47	-2.80	0.37
4580	0.66	0.52	-1.70	0.79	0.38	0.33	0.33	-7.90	0.70
4610	0.67	0.46	-3.30	0.79	0.34	0.24	0.24	-17.50	0.61
4630	0.77	0.69	1.70	0.89	0.56	0.47	0.47	8.10	0.70
4660	0.16	0.33	2.30	0.52	0.04	-0.43	-0.43	-48.20	0.02
4700	0.71	0.52	-1.40	0.78	0.41	0.36	0.36	12.60	0.70
4720	0.71	0.57	0.20	0.75	0.52	0.58	0.58	-0.10	0.72
4760	0.71	0.64	1.20	0.78	0.38	0.29	0.29	15.10	0.68
209759	0.71	0.56	3.20	0.79	0.51	0.45	0.45	4.10	0.73
209601	0.65	0.77	2.70	0.70	0.73	0.62	0.62	8.80	0.84
209742	0.69	0.69	-0.20	0.75	0.53	0.49	0.49	28.70	0.64
209734	0.56	0.65	2.40	0.60	0.55	0.46	0.46	25.20	0.65
208629	0.72	0.78	1.60	0.79	0.68	0.66	0.66	15.10	0.79
208637	0.24	0.40	-3.10	0.59	0.15	-0.40	-0.40	-45.10	0.15
209510	0.25	0.35	-2.80	0.65	0.10	-0.48	-0.48	-22.50	0.47
209320	0.29	0.35	-0.80	0.66	0.08	-0.45	-0.45	-20.30	0.46
208611	0.68	0.75	-0.80	0.73	0.49	0.39	0.39	47.90	0.47
209775	0.70	0.62	2.00	0.83	0.53	0.51	0.51	-2.80	0.65

Tab. 6.16: Monthly model efficiencies for calibration and validation for variant snow 96

ID	NSE cal [-]	logNSE cal [-]	PBIAS cal [%]	KGE cal [-]	SCAErr cal [%]	NSE val [-]	logNSE val [-]	PBIAS val [%]	KGE val [-]	SCAErr val [%]
4440	0.88	0.85	-1.10	0.92	3.81	0.70	0.62	1.70	0.81	4.85
4451	0.87	0.80	-0.10	0.93	2.98	0.75	0.70	9.40	0.82	4.96
4460	0.93	0.85	-0.80	0.96	2.83	0.80	0.75	6.80	0.87	5.25
4470	0.88	0.79	0.60	0.92	2.36	0.73	0.68	9.90	0.83	4.50
4560	0.95	0.90	-0.70	0.96	0.78	0.87	0.84	5.00	0.91	1.01
4566	0.79	0.66	0.70	0.81	0.79	0.78	0.58	2.60	0.74	1.41
4580	0.84	0.63	-1.10	0.92	0.80	0.64	0.36	-10.90	0.77	0.67
4610	0.75	0.60	-3.50	0.86	1.02	0.53	0.35	-11.20	0.73	0.39
4630	0.91	0.86	1.10	0.95	1.01	0.68	0.63	12.30	0.81	2.68
4660	0.51	0.51	9.40	0.74	1.81	0.06	-0.49	-44.90	0.29	5.54
4700	0.92	0.73	-2.80	0.94	2.19	0.60	0.49	9.50	0.78	3.31
4720	0.93	0.84	-1.50	0.96	1.77	0.80	0.78	6.40	0.87	3.60
4760	0.83	0.75	0.90	0.90	0.46	0.44	0.42	13.60	0.68	1.92
4290	0.92	0.85	4.30	0.91	0.00	0.78	0.53	13.40	0.83	1.70
4300	0.93	0.90	2.70	0.96	0.17	0.83	0.74	9.80	0.87	1.34
4320	0.88	0.87	2.40	0.92	0.00	0.64	0.53	15.50	0.77	1.77
4350	0.92	0.88	2.00	0.95	0.00	0.81	0.74	8.50	0.88	1.79
4370	0.90	0.85	1.60	0.92	0.00	0.78	0.58	5.30	0.88	1.61
4390	0.80	0.57	-3.10	0.89	0.43	0.67	0.37	21.40	0.71	0.80
4410	0.93	0.88	0.10	0.97	1.31	0.73	0.66	14.50	0.80	2.24
4420	0.94	0.89	-2.00	0.96	1.33	0.72	0.75	4.60	0.82	3.17
4480	0.95	0.88	1.70	0.95	0.35	0.64	0.67	11.10	0.78	1.92
4520	0.85	0.66	0.70	0.93	1.54	-0.13	-0.39	0.40	0.49	2.17
4530	0.87	0.66	-2.70	0.93	1.32	0.75	0.49	8.80	0.79	2.36
4540	0.90	0.80	0.20	0.93	0.71	0.48	0.36	0.30	0.68	1.29
4550	0.78	0.61	-0.30	0.73	1.32	0.43	0.48	-35.40	0.32	2.05
4570	0.91	0.83	-1.50	0.91	0.70	0.73	0.67	-5.90	0.78	0.51
4620	0.94	0.84	0.20	0.96	0.49	0.75	0.69	-5.40	0.86	0.69
4650	0.89	0.83	3.70	0.92	1.15	0.71	0.57	15.20	0.79	3.02
4690	0.93	0.88	0.70	0.95	0.50	0.79	0.73	11.20	0.85	2.84
4710	0.93	0.74	-3.50	0.95	1.99	0.63	0.42	-1.50	0.81	2.87
4740	0.93	0.80	-0.50	0.96	1.24	0.77	0.64	0.70	0.88	1.76
4770	0.78	0.70	1.00	0.87	0.27	0.60	0.45	8.60	0.74	0.77
4780	0.90	0.75	-1.90	0.95	0.33	0.71	0.54	5.50	0.84	1.38

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Tab. 6.16: Monthly model efficiencies for calibration and validation for variant snow 96 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4860	0.91	0.78	-0.80	0.93	1.34	0.62	0.52	10.90	0.77	2.15
4730	0.92	0.77	-2.00	0.95	1.32	0.79	0.54	-2.30	0.89	2.12
4400	0.83	0.61	-3.80	0.90	0.61	0.67	0.35	6.90	0.73	0.93
208645	0.90	0.84	1.40	0.94	0.00	0.61	0.48	9.10	0.67	1.31
209171	0.90	0.88	4.20	0.91	0.19	0.89	0.78	2.00	0.92	0.72
209601	0.92	0.85	3.50	0.92	0.00	0.80	0.67	11.60	0.85	2.21
209742	0.87	0.89	-1.10	0.86	0.35	0.74	0.73	23.40	0.74	1.06
209734	0.79	0.83	1.30	0.82	0.63	0.56	0.42	37.90	0.58	1.76
208629	0.93	0.89	1.60	0.96	0.34	0.86	0.77	13.80	0.84	1.25
208637	0.70	0.63	-3.50	0.85	0.93	0.31	-1.16	-47.20	0.34	0.85
209510	0.54	0.48	-1.50	0.78	1.49	0.40	-0.02	-14.40	0.71	1.45
209320	0.54	0.47	-1.50	0.78	1.56	0.38	-0.11	-15.60	0.70	1.54
208611	0.83	0.85	-5.80	0.83	1.23	0.32	0.47	47.10	0.43	1.08

Tab. 6.17: Daily model efficiencies for calibration and validation for variant snow 96

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]
4440	0.67	0.64	-0.60	0.80	0.80	0.57	0.41	4.30	0.71
4451	0.69	0.61	-0.10	0.82	0.82	0.58	0.51	9.30	0.77
4460	0.69	0.69	-0.90	0.82	0.82	0.61	0.57	6.70	0.78
4470	0.71	0.62	0.60	0.86	0.86	0.52	0.51	9.90	0.73
4560	0.68	0.74	-0.80	0.75	0.62	0.62	0.67	4.90	0.76
4566	0.36	0.51	0.70	0.69	0.44	0.44	0.43	2.60	0.51
4580	0.52	0.44	-1.00	0.75	0.32	0.32	0.28	-11.40	0.65
4610	0.53	0.41	-3.40	0.76	0.35	0.35	0.28	-11.00	0.67
4630	0.73	0.67	1.00	0.86	0.54	0.54	0.43	12.50	0.71
4660	-0.04	0.31	9.50	0.46	0.14	0.14	-0.48	-45.10	0.13
4700	0.68	0.45	-2.90	0.84	0.35	0.35	0.26	9.60	0.68
4720	0.67	0.56	-1.40	0.74	0.49	0.49	0.55	6.50	0.70
4760	0.62	0.55	1.00	0.76	0.23	0.23	0.24	14.10	0.61
209601	0.73	0.74	3.40	0.84	0.68	0.68	0.55	11.60	0.79

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Tab. 6.17: Daily model efficiencies for calibration and validation for variant snow 96 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]
209742	0.69	0.78	-1.20	0.73	0.59	0.60	23.50	0.70
209734	0.67	0.68	1.10	0.78	0.14	0.39	38.10	0.43
208629	0.74	0.77	1.50	0.81	0.70	0.64	13.90	0.78
208637	0.18	0.32	-3.20	0.61	0.17	-0.32	-47.00	0.16
209510	0.04	0.21	-1.40	0.55	0.01	-0.10	-14.30	0.41
209320	0.03	0.20	-1.40	0.55	-0.03	-0.17	-15.60	0.41
208611	0.66	0.72	-6.00	0.69	0.26	0.37	47.40	0.40

Tab. 6.18: Monthly model efficiencies for calibration and validation for variant distributed 96

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4300	0.93	0.91	0.10	0.95	0.68	0.87	0.72	7.80	0.86	0.88
4350	0.93	0.90	0.30	0.94	0.50	0.86	0.70	8.70	0.87	0.59
4370	0.94	0.86	3.30	0.96	0.49	0.84	0.51	11.20	0.86	0.37
4420	0.93	0.91	-1.60	0.96	2.15	0.72	0.78	4.10	0.81	6.40
4480	0.96	0.89	-2.70	0.95	0.74	0.73	0.73	1.90	0.86	1.80
4540	0.95	0.87	0.60	0.95	3.53	0.60	0.48	-1.30	0.81	0.97
4570	0.95	0.90	1.20	0.97	2.96	0.81	0.74	-5.50	0.87	0.40
4620	0.95	0.88	-4.00	0.90	2.91	0.79	0.74	-10.00	0.77	1.70
4650	0.88	0.82	1.90	0.93	1.91	0.72	0.58	12.30	0.81	2.00
4690	0.92	0.87	4.70	0.92	1.37	0.77	0.70	17.10	0.80	1.22
4710	0.91	0.73	-1.10	0.93	2.58	0.55	0.40	-0.60	0.76	2.11
4740	0.93	0.79	-1.50	0.95	1.60	0.75	0.63	-0.40	0.87	1.29
4770	0.80	0.70	-4.20	0.89	0.82	0.69	0.44	2.40	0.84	0.89
4780	0.90	0.77	1.50	0.95	0.68	0.71	0.52	12.40	0.81	0.63
4730	0.92	0.78	-1.10	0.94	1.66	0.74	0.51	1.60	0.86	1.27
4470	0.83	0.80	11.70	0.83	4.78	0.61	0.65	22.20	0.68	5.42
209171	0.92	0.90	3.90	0.93	0.52	0.91	0.74	3.40	0.91	0.89
209601	0.92	0.88	1.40	0.96	0.73	0.84	0.71	7.00	0.89	1.14
209742	0.87	0.90	-4.90	0.83	1.21	0.80	0.70	19.20	0.79	1.36
208629	0.93	0.91	2.80	0.94	1.56	0.86	0.70	16.10	0.83	1.27

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Tab. 6.18: Monthly model efficiencies for calibration and validation for variant distributed 96 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
208637	0.70	0.65	-3.00	0.85	1.61	0.26	-1.18	-48.00	0.31	0.77

Tab. 6.19: Daily model efficiencies for calibration and validation for variant distributed 96

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[-]
4470	0.68	0.68	11.6	0.81	0.81	0.45	0.5	22.1	0.65	
209601	0.75	0.77	1.3	0.81	0.81	0.71	0.59	7	0.82	
209742	0.67	0.8	-5.1	0.65	0.65	0.65	0.6	19.3	0.72	
208629	0.75	0.82	2.8	0.76	0.76	0.71	0.62	16.1	0.78	
208637	0.46	0.5	-2.7	0.7	0.7	0.24	-0.2	-47.9	0.18	

Tab. 6.20: Monthly model efficiencies for calibration and validation for variant distributed 91

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4300	0.93	0.87	3.60	0.95	-	0.86	0.76	2.20	0.88	2.58
4350	0.93	0.83	7.20	0.92	-	0.86	0.76	0.30	0.89	2.11
4370	0.93	0.67	8.80	0.90	-	0.86	0.58	2.90	0.90	1.81
4420	0.96	0.90	-0.20	0.96	-	0.77	0.75	2.10	0.79	3.24
4480	0.97	0.90	2.20	0.95	-	0.71	0.73	9.30	0.81	1.92
4540	0.95	0.88	1.40	0.97	-	0.43	0.06	-12.00	0.75	1.42
4570	0.96	0.92	-0.30	0.91	-	0.72	0.57	-14.40	0.76	1.88
4620	0.97	0.90	0.50	0.96	-	0.79	0.73	-7.50	0.86	1.63
4650	0.89	0.79	2.30	0.94	-	0.75	0.58	9.80	0.81	2.20
4690	0.93	0.83	0.40	0.95	-	0.83	0.76	5.70	0.87	1.69
4710	0.91	0.73	-3.80	0.94	-	0.65	0.43	-6.10	0.82	2.29
4740	0.95	0.81	-0.90	0.97	-	0.78	0.61	-5.40	0.86	1.44
4770	0.86	0.68	1.40	0.92	-	0.57	0.45	1.20	0.75	1.58
4780	0.91	0.82	3.20	0.94	-	0.74	0.51	7.00	0.83	0.99

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Tab. 6.20: Monthly model efficiencies for calibration and validation for variant distributed 91 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4730	0.94	0.81	-2.40	0.95	-	0.73	0.51	0.40	0.86	3.57
4470	0.92	0.83	0.30	0.94	-	0.77	0.66	9.10	0.86	1.94
209171	0.92	0.84	3.20	0.93	-	0.90	0.78	-1.60	0.92	2.06
208629	0.93	0.85	-1.00	0.96	-	0.90	0.79	1.50	0.94	2.17
208637	0.84	0.62	-2.90	0.90	-	0.00	-1.73	-52.10	0.17	0.68

Tab. 6.21: Daily model efficiencies for calibration and validation for variant distributed 91

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[-]	[-]	[%]	[-]
4470	0.75	0.69	0.2	0.88	0.59	0.54	9.1	0.75
208629	0.78	0.73	-1	0.85	0.73	0.64	1.5	0.81
208637	0.7	0.39	-2.3	0.75	0.11	-0.48	-51.8	0.08

Tab. 6.22: Monthly model efficiencies for calibration and validation for variant distributed 86

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4300	0.91	0.83	-1.00	0.92	-	0.88	0.75	6.60	0.91	1.46
4350	0.90	0.72	0.60	0.88	-	0.88	0.74	7.50	0.90	1.00
4370	0.90	0.59	3.70	0.89	-	0.86	0.56	11.50	0.86	0.85
4420	0.92	0.89	-1.30	0.93	-	0.79	0.77	1.30	0.82	2.91
4480	0.95	0.88	-3.70	0.93	-	0.77	0.72	4.40	0.88	1.39
4540	0.80	0.77	2.40	0.90	-	0.51	0.27	-4.30	0.72	1.69
4570	0.87	0.84	-1.60	0.88	-	0.77	0.65	-5.70	0.84	0.40
4620	0.93	0.86	-1.30	0.93	-	0.77	0.71	-5.70	0.86	0.70
4650	0.86	0.80	1.70	0.91	-	0.73	0.64	9.40	0.84	3.54
4690	0.92	0.85	-0.70	0.92	-	0.83	0.75	1.60	0.90	2.53
4710	0.85	0.69	1.40	0.90	-	0.67	0.41	4.90	0.82	2.22
4740	0.92	0.78	-5.60	0.91	-	0.77	0.65	-2.30	0.88	1.13

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Tab. 6.22: Monthly model efficiencies for calibration and validation for variant distributed 86 (Continuation)

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val	SCAErr val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]	[%]
4770	0.80	0.51	-5.00	0.88	-	0.14	0.39	12.00	0.52	1.35
4780	0.90	0.80	0.20	0.92	-	0.72	0.56	6.20	0.85	0.99
4730	0.90	0.77	-4.40	0.89	-	0.71	0.50	3.30	0.84	1.91
4470	0.92	0.85	0.80	0.96	-	0.74	0.71	9.60	0.81	2.34
209171	0.92	0.77	1.20	0.88	-	0.93	0.77	3.40	0.95	1.34
208629	0.90	0.83	-2.80	0.91	-	0.88	0.80	6.30	0.88	2.60
208637	0.71	0.45	-7.50	0.81	-	0.04	-1.24	-46.10	0.19	0.85

Tab. 6.23: Daily model efficiencies for calibration and validation for variant distributed 86

ID	NSE cal	logNSE cal	PBIAS cal	KGE cal	SCAErr cal	NSE val	logNSE val	PBIAS val	KGE val
	[-]	[-]	[%]	[-]	[%]	[-]	[-]	[%]	[-]
4470	0.79	0.73	0.7	0.85	-	0.58	0.59	9.5	0.75
208629	0.73	0.72	-2.9	0.78	-	0.73	0.68	6.2	0.85
208637	0.14	0.22	-6.7	0.43	-	0.03	-0.35	-46	0.03

Tab. 6.24: Median for monthly model efficiencies for the calibration period

calibration variant	NSE [-]	logNSE [-]	PBIAS [%]	KGE [-]	SCAErr [%]
1 lumped 96	0.87	0.80	0.40	0.91	1.90
1 lumped 91	0.88	0.79	-1.30	0.92	-
1 lumped 86	0.86	0.75	-1.15	0.90	-
2 semi 96	0.89	0.80	0.70	0.92	1.53
2 semi 91	0.91	0.81	-0.40	0.93	-
2 semi 86	0.88	0.76	-2.85	0.88	-
3 snow 01-11	0.89	0.82	1.00	0.93	0.89
3 snow 96	0.90	0.83	-0.10	0.92	0.80
4 distributed 96	0.92	0.87	0.30	0.94	1.56
4 distributed 91	0.93	0.83	0.50	0.94	-
4 distributed 86	0.90	0.80	-1.00	0.91	-

Tab. 6.25: Median for monthly model efficiencies for the validation period

calibration variant	NSE [-]	logNSE [-]	PBIAS [%]	KGE [-]	SCAErr [%]
1 lumped 96	0.69	0.55	3.80	0.79	2.43
1 lumped 91	0.68	0.58	-2.70	0.80	3.23
1 lumped 86	0.66	0.54	1.10	0.77	2.41
2 semi 96	0.72	0.55	6.30	0.77	1.62
2 semi 91	0.71	0.57	-3.40	0.82	1.77
2 semi 86	0.71	0.59	0.20	0.84	2.02
3 snow 01-11	0.71	0.59	7.70	0.79	1.52
3 snow 96	0.71	0.54	6.90	0.79	1.76
4 distributed 96	0.75	0.70	4.10	0.83	1.22
4 distributed 91	0.77	0.61	1.20	0.86	1.92
4 distributed 86	0.77	0.65	4.40	0.85	1.39

Tab. 6.26: Median for daily model efficiencies for the calibration period

calibration variant	NSE [-]	logNSE [-]	PBIAS [%]	KGE [-]
1 lumped 96	0.61	0.55	0.00	0.74
1 lumped 91	0.67	0.59	-1.80	0.81
1 lumped 86	0.67	0.53	-2.40	0.76
2 semi 96	0.61	0.59	1.75	0.73
2 semi 91	0.66	0.61	-1.40	0.78
2 semi 86	0.71	0.56	-4.30	0.76
3 snow 01-11	0.69	0.58	0.80	0.78
3 snow 96	0.67	0.61	-0.80	0.76
4 distributed 96	0.68	0.77	1.30	0.76
4 distributed 91	0.75	0.69	-1.00	0.85
4 distributed 86	0.73	0.72	-2.90	0.78

Tab. 6.27: Median for daily model efficiencies for the validation period

calibration variant	NSE [-]	logNSE [-]	PBIAS [%]	KGE [-]
1 lumped 96	0.43	0.38	3.70	0.63
1 lumped 91	0.43	0.40	-0.55	0.70
1 lumped 86	0.41	0.33	1.30	0.63
2 semi 96	0.39	0.40	9.20	0.63
2 semi 91	0.49	0.44	-0.80	0.72
2 semi 86	0.38	0.33	0.60	0.69
3 snow 01-11	0.52	0.45	8.10	0.68
3 snow 96	0.44	0.41	6.70	0.68
4 distributed 96	0.65	0.59	16.10	0.72
4 distributed 91	0.59	0.54	1.50	0.75
4 distributed 86	0.58	0.59	6.20	0.75

6.2.2 Parameter values

Tab. 6.28: Parameter values for calibration variant lumped 96 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T _R [°C]	T _S [°C]	T _M [°C]	LP [-]	FC [mm]	β [-]
4440	0.906	2.629	1.531	0.213	-1.041	0.529	180.055	3.419
4451	0.919	4.071	1.696	-2.218	1.197	0.677	171.447	3.675
4460	1.012	2.513	2.528	-0.708	-1.237	0.760	231.877	4.235
4470	0.906	1.399	2.251	-0.503	-1.706	0.588	180.250	2.712
4560	1.057	3.331	2.645	-2.492	0.378	0.843	177.065	4.221
4566	0.904	2.982	2.775	0.143	0.060	0.892	236.188	3.741
4580	0.910	1.286	2.950	-0.644	-0.550	0.511	286.786	2.759
4610	1.285	4.643	1.992	-2.897	1.705	0.509	471.052	2.926
4630	0.907	2.585	1.163	-2.407	0.888	0.906	255.622	4.771
4660	0.902	3.369	2.973	0.807	-1.040	0.545	389.138	6.012
4700	1.015	3.430	2.434	-0.704	0.385	0.953	250.737	6.502
4720	1.144	1.663	1.077	-0.453	-0.834	0.703	179.720	3.650
4760	0.901	1.516	2.249	-0.218	-0.591	0.730	194.132	4.166
4290	0.910	2.927	2.889	0.413	-0.424	0.705	188.511	3.878
4300	0.904	3.329	2.258	0.974	0.508	0.737	180.165	3.610
4320	0.907	4.064	2.519	0.068	0.601	0.762	229.178	4.161
4350	0.915	3.499	1.322	-1.854	1.438	0.834	241.264	5.027
4370	0.902	2.488	2.225	0.695	0.531	0.401	203.463	2.037
4390	0.912	4.455	1.280	0.446	0.660	0.819	254.700	5.016
4410	0.982	1.617	2.180	-1.900	-1.788	0.882	145.911	3.344
4420	0.902	1.594	2.685	-1.348	-1.873	0.440	111.951	1.635
4480	0.907	2.180	2.208	-0.689	-0.890	0.586	191.602	2.697
4520	0.975	2.750	2.998	0.587	-1.436	0.661	60.585	1.361
4530	0.908	2.197	2.146	0.759	-1.707	0.626	212.620	2.548
4540	1.207	3.689	1.518	-0.957	0.085	0.216	201.411	0.816
4550	0.907	1.104	2.449	-0.534	-1.851	0.734	208.216	4.209
4570	1.025	3.991	1.664	-2.139	1.547	0.665	277.688	2.367
4620	0.903	1.259	2.565	-1.393	-0.511	0.641	246.136	2.879
4650	0.910	4.967	2.336	-0.515	0.655	0.701	202.488	3.077
4690	0.912	2.224	2.635	0.486	-0.187	0.650	162.471	2.907
4710	1.069	4.378	2.353	0.172	0.391	0.894	240.316	6.375
4740	0.966	1.362	2.925	0.430	-1.038	0.817	221.532	4.857

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Tab. 6.28: Parameter values for calibration variant lumped 96 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4770	0.902	1.162	2.580	-0.449	-0.812	0.664	237.321	3.550
4780	0.934	1.208	2.951	-0.650	-1.048	0.763	216.393	3.848
4860	0.959	0.961	1.574	-0.945	-0.905	0.574	379.419	2.933
4730	1.006	1.330	2.936	0.660	-1.648	0.840	229.711	5.054
4400	0.903	1.624	1.338	0.853	0.048	0.668	257.967	4.000
208645	0.918	1.894	1.184	-2.893	1.359	0.798	184.343	4.145
209171	0.905	0.734	2.833	-1.806	-1.874	0.820	189.573	4.127
209601	0.906	1.672	2.957	-1.309	-0.879	0.765	168.655	3.872
209742	0.946	1.565	1.377	-2.831	0.954	0.951	114.315	4.700
209734	0.907	3.034	1.832	-2.549	1.993	0.502	22.410	6.425
208629	0.932	2.339	1.356	-2.916	0.815	0.930	140.526	4.913
208637	1.294	2.842	2.668	-0.234	1.300	0.464	504.641	2.866
209510	0.905	4.262	1.812	-1.303	1.621	0.401	312.989	2.198
209320	0.998	4.421	2.310	-0.018	1.153	0.320	414.511	1.809
208611	0.925	3.271	2.459	-2.105	1.358	0.987	81.005	4.329

Tab. 6.29: Parameter values for calibration variant lumped 96 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4440	0.757	10.881	229.911	80.819	0.328	23.541	45.721
4451	1.124	11.599	207.654	47.515	0.273	12.253	47.318
4460	0.519	8.853	238.090	39.668	0.199	20.321	49.979
4470	1.855	8.681	120.397	47.719	0.223	10.397	34.542
4560	0.585	6.226	135.815	59.392	0.209	10.281	24.985
4566	1.203	4.537	226.175	64.617	0.481	23.369	6.868
4580	1.654	8.434	195.515	26.022	0.135	5.200	27.657
4610	0.713	3.166	246.088	36.279	0.214	8.320	4.122
4630	0.714	11.829	98.258	45.755	0.726	19.471	20.129
4660	1.916	4.133	125.702	12.216	0.080	0.134	17.589
4700	0.410	13.665	225.202	11.353	0.335	9.462	11.674
4720	1.882	4.452	158.976	54.270	0.225	15.404	38.736
4760	0.083	5.283	198.559	70.987	0.221	12.417	44.244
4290	0.593	6.609	187.830	79.863	0.251	1.195	29.036
4300	0.851	4.392	107.546	77.736	0.347	6.424	16.108
4320	0.880	5.244	153.945	15.246	0.203	10.818	44.861
4350	1.465	7.341	206.242	41.036	0.225	5.500	35.183
4370	1.482	5.779	140.793	35.750	0.134	10.828	37.281
4390	0.979	8.975	181.429	92.316	0.099	4.622	30.462
4410	0.702	6.460	82.296	56.519	0.809	28.343	42.530
4420	0.541	6.095	79.254	21.143	0.580	14.342	39.739
4480	0.869	6.614	159.990	86.746	0.249	1.078	47.563
4520	1.597	24.447	230.520	80.902	6.747	7.172	9.711
4530	0.156	7.384	158.611	75.167	0.307	11.502	36.652
4540	1.190	8.850	168.884	77.160	1.821	25.617	46.446
4550	0.514	2.634	146.869	72.269	0.347	16.202	31.208
4570	1.814	9.632	214.310	70.837	0.488	17.037	49.488
4620	1.215	5.107	227.121	49.353	0.236	12.950	44.469
4650	0.938	8.572	153.766	39.932	0.554	14.372	45.501
4690	0.262	8.537	129.231	16.181	0.407	23.217	43.078
4710	0.690	10.395	192.714	18.660	0.335	14.348	24.525
4740	1.679	4.950	207.705	43.681	0.184	11.866	37.402

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Tab. 6.29: Parameter values for calibration variant lumped 96 (2/2) (Continuation)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4770	1.356	6.155	160.621	16.684	0.087	7.166	43.905
4780	0.760	5.530	126.260	45.537	0.321	10.009	25.139
4860	0.637	4.135	120.412	7.393	0.187	0.383	32.906
4730	1.578	5.782	149.179	48.511	0.193	7.273	16.430
4400	1.147	6.979	193.498	22.020	0.037	0.499	18.731
208645	1.414	8.045	130.273	42.203	0.120	6.279	36.171
209171	0.508	8.960	223.902	31.143	0.154	14.563	39.099
209601	0.439	8.838	137.897	29.340	0.243	5.280	48.730
209742	1.761	11.784	99.975	32.864	0.312	11.358	39.375
209734	1.192	29.183	67.015	34.417	0.456	18.761	20.565
208629	0.963	12.396	147.234	32.129	0.251	2.951	40.769
208637	1.049	8.691	214.397	31.530	0.057	4.947	35.525
209510	0.286	6.371	196.471	63.223	0.208	22.776	16.080
209320	0.776	3.145	175.468	39.475	0.215	18.692	8.278
208611	0.880	11.582	48.873	15.650	0.272	5.547	4.857

Tab. 6.30: Parameter values for calibration variant lumped 91 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4440	0.915	1.343	1.104	-2.918	-0.502	0.445	188.572	2.843
4451	1.112	1.199	1.623	-2.279	-1.434	0.371	161.824	2.459
4460	1.089	1.493	2.496	-2.167	-1.554	0.773	256.844	4.007
4470	0.934	2.265	1.159	-1.713	-0.269	0.691	241.744	3.465
4560	1.068	1.413	2.489	-1.903	-1.592	0.948	235.041	5.397
4566	0.902	3.061	2.437	0.684	-0.158	0.892	259.249	3.967
4580	0.908	2.064	1.680	0.203	-0.011	0.621	300.636	3.515
4610	1.288	2.102	2.814	-0.369	-0.472	0.345	403.796	2.294
4630	0.985	3.810	1.815	-2.878	0.177	0.633	224.798	2.450
4660	1.045	0.591	1.078	-2.621	-1.845	0.598	343.456	9.537
4700	1.071	2.791	2.221	-1.910	0.008	0.866	252.265	4.782
4720	1.217	1.142	1.581	-2.832	-1.097	0.899	289.296	5.327
4760	0.930	4.210	1.433	-0.427	0.566	0.827	243.304	5.414
4290	0.921	4.440	1.307	-1.771	0.549	0.857	238.978	5.780
4300	0.972	1.776	1.742	-1.248	-0.145	0.709	223.876	3.686
4320	0.929	3.764	2.047	-0.267	0.481	0.749	292.155	4.440
4350	1.114	1.651	1.871	-2.813	-0.255	0.660	288.633	3.541
4370	1.115	1.978	1.051	-2.086	0.305	0.507	257.777	2.721
4390	0.936	1.996	1.391	0.754	-0.307	0.806	267.323	5.597
4410	0.944	2.960	1.020	-2.649	-0.379	0.982	213.935	4.849
4420	0.909	1.403	1.627	-2.842	-0.987	0.907	225.091	4.470
4480	0.987	1.457	1.985	-0.381	-1.580	0.741	248.621	3.522
4520	1.422	2.907	2.011	-1.348	-1.650	0.063	105.041	0.612
4530	0.914	2.483	1.779	-0.857	-0.491	0.832	358.257	3.898
4540	1.305	3.834	2.761	-2.217	0.126	0.497	270.242	1.430
4550	0.929	3.497	1.730	-2.673	0.346	0.997	372.737	8.152
4570	1.168	3.829	2.908	-2.223	0.164	0.502	246.301	2.010
4620	0.947	1.308	2.251	-1.866	-1.044	0.586	234.604	2.857
4650	0.997	3.067	1.818	-1.151	-0.255	0.736	249.917	3.563
4690	0.991	2.590	1.026	-2.047	-0.146	0.861	243.498	4.392
4710	1.077	1.247	1.226	0.128	-1.838	0.850	256.252	5.233
4740	1.002	0.988	1.520	0.765	-1.822	0.755	231.730	4.378

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Tab. 6.30: Parameter values for calibration variant lumped 91 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4770	1.122	3.793	1.959	0.154	0.233	0.700	301.829	3.953
4780	1.118	1.589	1.053	-1.656	-0.854	0.826	282.338	4.588
4860	1.069	2.916	1.690	-0.131	0.768	0.602	420.795	3.023
4730	1.116	2.135	2.156	-0.369	-0.710	0.780	245.235	4.459
4400	0.950	1.960	2.332	-0.624	-0.046	0.843	273.527	6.524
208645	0.981	1.647	1.165	-2.192	-0.037	0.603	223.038	3.078
209171	1.220	1.628	1.136	-2.850	-0.672	0.558	211.133	2.579
209601	0.950	1.329	2.422	-2.365	-1.017	0.893	245.941	5.568
208629	1.231	2.254	1.058	-2.949	-0.310	0.779	235.785	3.608
208637	1.020	2.210	1.883	0.697	1.022	0.473	429.776	2.792
209510	1.268	2.279	2.388	-0.519	-0.490	0.390	348.761	2.271
209320	1.110	3.856	1.106	-1.107	0.427	0.399	247.330	2.436
208611	1.440	1.143	1.058	-2.795	-1.599	0.999	197.765	4.227

Tab. 6.31: Parameter values for calibration variant lumped 91 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4440	1.260	8.845	224.623	56.601	0.252	11.094	11.357
4451	0.256	9.011	230.953	51.149	0.462	10.657	36.965
4460	0.813	10.033	219.111	60.034	0.181	4.663	37.365
4470	0.918	7.580	237.620	71.851	0.189	16.230	46.353
4560	0.910	5.460	143.377	94.415	0.149	5.662	35.953
4566	0.407	4.407	166.551	6.360	0.457	26.455	7.214
4580	0.244	6.651	242.580	55.603	0.138	7.564	32.469
4610	1.726	5.287	246.313	38.633	0.138	6.024	27.691
4630	0.435	10.934	197.990	81.385	0.525	13.416	47.113
4660	1.258	7.149	198.273	81.437	0.149	5.286	37.965
4700	0.786	7.539	241.424	62.481	0.298	8.557	48.067
4720	0.788	5.199	227.156	91.364	0.081	10.457	32.963
4760	1.324	6.755	240.898	97.552	0.198	3.810	41.361
4290	0.136	10.290	235.649	86.590	0.237	4.552	21.777
4300	0.232	5.202	227.596	49.022	0.263	5.238	31.926
4320	0.980	6.157	242.730	88.005	0.127	4.133	45.447
4350	0.712	4.367	240.964	36.651	0.118	7.795	33.654
4370	1.270	6.214	220.561	50.279	0.057	4.330	14.595
4390	0.848	6.886	249.730	64.120	0.026	4.784	24.886
4410	1.416	13.194	225.319	41.333	0.473	12.785	27.137
4420	0.739	7.589	229.885	33.580	0.408	12.938	28.367
4480	1.417	6.615	246.192	25.116	0.256	5.352	46.155
4520	0.807	22.407	249.307	91.823	4.613	21.604	46.852
4530	1.221	21.182	200.540	19.764	0.543	26.638	21.209
4540	0.460	17.525	240.177	35.011	1.061	7.184	39.923
4550	0.398	2.952	240.130	17.711	0.200	5.466	10.014
4570	1.179	7.802	194.485	57.298	0.593	9.311	34.542
4620	0.795	7.174	228.491	88.792	0.200	13.494	40.436
4650	1.416	7.030	245.174	85.339	0.466	3.025	43.269
4690	0.702	10.208	242.093	65.626	0.225	0.476	45.335
4710	1.295	6.065	244.080	19.484	0.263	13.987	16.827
4740	0.426	7.193	202.747	17.569	0.151	11.473	49.120
4770	1.363	4.545	237.503	51.075	0.058	8.866	2.499
4780	1.435	8.259	245.073	46.192	0.292	9.002	28.268

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Tab. 6.31: Parameter values for calibration variant lumped 91 (2/2) (Continuation)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4860	0.142	4.680	217.548	58.725	0.196	6.041	23.818
4730	0.160	6.896	230.469	77.568	0.211	3.292	22.139
4400	0.854	5.932	247.430	86.063	0.049	9.140	34.834
208645	1.270	8.494	225.807	67.975	0.052	9.076	47.962
209171	1.943	7.606	226.653	24.610	0.137	4.930	31.463
209601	1.655	10.275	232.918	73.208	0.243	14.537	48.279
208629	1.495	7.011	214.811	69.756	0.178	11.560	40.348
208637	0.880	2.034	233.387	99.151	0.099	10.192	21.801
209510	1.398	7.501	211.158	17.113	0.170	7.650	8.294
209320	0.791	12.231	239.496	19.581	0.197	2.489	28.925
208611	0.978	7.930	141.712	61.837	0.077	5.869	19.092

Tab. 6.32: Parameter values for calibration variant lumped 86 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4440	0.902	2.155	2.525	-2.700	0.280	0.958	297.633	8.362
4451	1.146	2.781	1.449	-2.680	0.670	0.835	201.626	3.956
4460	1.051	2.639	1.531	-2.811	0.650	0.906	272.634	4.974
4470	1.040	2.482	1.326	-2.931	0.556	0.756	255.198	3.848
4560	1.242	3.716	1.375	-2.739	0.801	0.840	238.982	4.077
4566	1.014	2.058	2.091	-2.153	-0.163	0.957	279.127	4.455
4580	1.476	1.342	1.081	0.489	-1.114	0.463	459.956	2.585
4610	1.388	3.870	2.125	-2.763	1.423	0.407	475.760	2.381
4630	1.073	2.001	1.731	-2.849	-1.700	0.790	233.345	4.401
4660	0.919	2.750	2.669	0.887	-1.006	0.674	376.103	8.229
4700	0.978	3.850	2.241	-2.813	1.051	0.984	259.360	6.669
4720	0.936	2.228	2.810	0.940	-0.800	0.900	256.080	5.057
4760	1.392	1.872	1.235	-0.757	-0.757	0.764	316.600	4.800
4290	0.942	3.240	2.636	-1.917	0.384	0.910	256.358	6.391
4300	1.023	2.256	1.913	-2.472	0.082	0.899	288.649	4.964
4320	1.376	2.844	1.272	0.050	-0.541	0.679	382.906	3.919
4350	1.005	2.933	1.342	-2.413	1.024	0.852	267.451	4.731
4370	1.404	2.441	1.643	-0.958	0.479	0.595	330.125	2.937
4390	1.357	3.438	1.503	-0.149	0.397	0.593	332.425	3.968
4410	1.112	2.964	1.137	-2.996	-0.113	0.939	235.622	3.976
4420	1.095	3.399	1.165	-2.675	0.051	0.768	248.661	2.995
4480	0.912	2.575	2.160	-2.437	0.810	0.897	239.100	5.088
4520	1.462	4.543	1.008	-1.056	0.670	0.850	201.853	1.669
4530	1.429	4.387	1.238	-0.617	-0.199	0.679	444.771	3.251
4540	1.378	4.219	1.048	-0.052	0.339	0.603	259.274	1.703
4550	0.912	1.938	2.489	0.061	-0.394	0.895	248.164	5.814
4570	1.043	2.517	1.551	-2.449	0.562	0.839	261.408	3.718
4620	0.935	1.453	1.633	-1.298	0.238	0.734	232.836	3.730
4650	0.995	3.599	1.885	-1.653	-0.346	0.907	296.140	6.777
4690	1.098	1.872	1.313	-2.069	-0.666	0.954	309.928	6.299
4710	0.981	1.102	1.774	0.791	-1.961	0.948	289.278	6.263
4740	1.177	4.299	1.452	-2.070	1.230	0.797	267.730	4.365
4770	1.467	1.902	1.145	0.133	-0.425	0.683	319.576	3.922
4780	1.113	2.796	1.301	-0.737	0.438	0.822	279.583	4.678
4860	1.360	2.526	2.666	-0.322	-0.184	0.316	535.203	1.800
4730	1.003	3.340	2.466	-2.773	0.687	0.942	296.723	6.155

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Tab. 6.32: Parameter values for calibration variant lumped 86 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4400	1.355	3.952	1.056	-0.921	1.048	0.717	311.326	5.048
208645	1.178	2.850	2.423	-1.922	0.333	0.509	238.293	2.385
209171	1.438	3.815	1.381	-2.140	0.218	0.756	265.322	3.685
208629	1.422	4.056	1.427	-2.341	-0.343	0.811	276.849	3.990
208637	1.487	2.593	2.298	0.384	1.115	0.391	519.627	2.507
209510	1.191	3.754	2.090	-1.543	1.097	0.398	401.456	2.037
209320	1.059	2.563	1.285	-1.548	0.768	0.496	328.274	2.368
208611	1.182	3.313	1.423	-2.368	-0.352	0.989	174.479	3.585

Tab. 6.33: Parameter values for calibration variant lumped 86 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4440	0.679	9.501	204.684	51.629	0.257	12.319	43.512
4451	1.608	9.459	187.501	82.528	0.361	10.577	33.858
4460	1.074	8.889	186.342	86.156	0.160	4.293	38.669
4470	0.417	7.817	181.322	87.238	0.210	0.957	37.442
4560	0.393	6.044	212.756	58.268	0.130	12.319	20.837
4566	1.574	20.099	176.115	13.103	0.437	6.176	37.464
4580	0.312	9.341	185.603	66.434	0.071	5.914	9.778
4610	0.194	6.061	149.042	66.338	0.060	3.344	17.267
4630	1.099	16.443	197.360	62.954	0.518	9.906	11.239
4660	1.435	5.695	217.299	38.622	0.130	23.783	8.959
4700	0.123	7.716	224.011	33.954	0.293	19.186	37.933
4720	1.956	5.168	201.634	16.300	0.095	8.149	35.692
4760	0.635	5.826	223.491	66.629	0.185	13.228	14.842
4290	0.510	8.461	228.033	72.067	0.175	7.798	27.435
4300	1.044	5.941	194.828	32.977	0.178	3.578	31.370
4320	1.656	3.291	175.681	95.377	0.114	6.321	23.443
4350	1.171	5.011	158.197	59.661	0.101	3.849	7.608
4370	1.964	5.273	219.449	46.414	0.047	0.305	32.491
4390	0.647	4.511	214.496	85.053	0.049	4.751	1.124
4410	0.352	10.296	133.610	68.516	0.441	6.360	30.040
4420	0.222	15.084	219.797	2.502	0.302	6.706	44.383
4480	1.280	5.964	180.005	57.576	0.194	1.143	29.623
4520	1.295	17.387	242.625	46.480	2.944	17.348	44.759
4530	0.834	25.353	211.374	15.653	0.628	26.428	9.476
4540	0.648	11.861	243.698	86.385	1.216	5.090	13.862
4550	1.136	5.056	147.245	48.645	0.133	28.095	41.122
4570	0.162	8.442	227.059	71.201	0.538	4.822	49.906
4620	0.741	7.554	204.547	76.493	0.261	10.944	25.107
4650	1.713	10.546	188.306	81.794	0.487	6.792	8.611
4690	1.336	7.538	229.362	43.147	0.269	5.327	27.634
4710	1.792	7.309	209.190	25.918	0.251	7.348	23.912
4740	0.111	7.203	207.526	84.331	0.134	9.969	21.198
4770	0.008	3.249	235.409	85.444	0.102	10.749	1.952
4780	0.647	8.837	189.462	53.164	0.264	3.769	17.336
4860	0.209	5.261	184.787	95.161	0.140	8.097	13.311
4730	0.514	6.733	218.685	57.578	0.235	17.149	23.135
4400	1.023	7.645	237.563	16.767	0.105	11.900	18.542
208645	0.991	7.731	140.142	63.270	0.083	8.276	30.943
209171	0.164	5.387	150.085	18.947	0.113	2.207	49.837

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Tab. 6.33: Parameter values for calibration variant lumped 86 (2/2) (Continuation)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
208629	0.212	7.708	157.010	32.293	0.208	7.314	35.606
208637	1.067	3.063	234.858	30.183	0.197	11.605	4.867
209510	0.620	2.410	236.905	55.112	0.217	15.888	5.512
209320	1.205	7.582	243.340	64.985	0.213	3.949	16.237
208611	1.392	7.035	181.045	20.066	0.127	13.984	6.156

Tab. 6.34: Parameter values for calibration variant semi-distributed 96-0 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4470	0.906	1.399	2.251	-0.503	-1.706	0.588	180.250	2.712
4560	1.057	3.331	2.645	-2.492	0.378	0.843	177.065	4.221
4610	1.285	4.643	1.992	-2.897	1.705	0.509	471.052	2.926
4660	0.902	3.369	2.973	0.807	-1.040	0.545	389.138	6.012
4700	1.015	3.430	2.434	-0.704	0.385	0.953	250.737	6.502
4720	1.144	1.663	1.077	-0.453	-0.834	0.703	179.720	3.650
4760	0.901	1.516	2.249	-0.218	-0.591	0.730	194.132	4.166
4290	0.917	2.298	2.172	-2.627	0.146	0.792	209.868	4.396
4300	0.924	4.739	2.440	-2.654	1.918	0.790	160.956	3.736
4320	0.932	4.002	2.092	-2.082	1.161	0.753	182.360	4.673
4350	0.905	0.788	2.588	-1.777	-1.409	0.728	167.829	3.482
4370	0.915	1.354	2.407	-1.219	-0.486	0.622	184.466	3.099
4390	0.951	0.871	1.075	-2.716	-0.505	0.849	212.614	5.260
4420	0.917	1.530	2.165	-2.635	-1.940	0.897	195.323	4.266
4480	0.918	1.382	2.774	-0.282	-1.912	0.829	259.757	4.346
4530	0.901	4.341	2.057	0.899	-1.718	0.761	249.805	3.547
4540	0.907	3.026	1.792	-2.994	0.701	0.597	109.789	1.931
4550	0.915	4.297	2.324	0.986	-0.278	0.435	224.770	2.609
4570	1.072	4.279	1.584	-2.959	1.148	0.201	202.130	1.245
4620	0.904	2.702	1.570	0.799	-0.323	0.513	224.862	2.406
4650	0.916	3.225	2.989	-2.518	0.400	0.720	218.146	3.075
4690	0.901	1.498	2.437	-0.529	-1.392	0.756	181.049	3.265
4710	0.916	1.730	2.300	-0.080	-1.166	0.881	189.320	5.153
4740	0.914	1.929	2.619	-0.292	-0.600	0.825	214.389	5.050
4770	1.111	2.603	1.413	-2.059	0.603	0.708	253.021	3.999
4780	0.969	1.935	2.569	-1.767	-0.731	0.856	205.719	5.094
4730	1.137	1.929	1.613	-0.536	-0.716	0.731	177.559	3.450
4400	0.918	2.066	1.655	-2.138	1.211	0.698	227.417	4.383
208645	0.933	1.675	2.605	-2.333	-0.399	0.773	192.204	4.410
209171	0.908	1.765	2.601	-1.287	-0.117	0.784	172.041	4.039
209601	0.906	1.672	2.957	-1.309	-0.879	0.765	168.655	3.872
209742	0.946	1.565	1.377	-2.831	0.954	0.951	114.315	4.700
209734	0.907	3.034	1.832	-2.549	1.993	0.502	22.410	6.425
208629	0.932	2.339	1.356	-2.916	0.815	0.930	140.526	4.913
208637	1.294	2.842	2.668	-0.234	1.300	0.464	504.641	2.866

Tab. 6.35: Parameter values for calibration variant semi-distributed 96 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4470	1.855	8.681	120.397	47.719	0.223	10.397	34.542
4560	0.585	6.226	135.815	59.392	0.209	10.281	24.985
4610	0.713	3.166	246.088	36.279	0.214	8.320	4.122
4660	1.916	4.133	125.702	12.216	0.080	0.134	17.589
4700	0.410	13.665	225.202	11.353	0.335	9.462	11.674
4720	1.882	4.452	158.976	54.270	0.225	15.404	38.736
4760	0.083	5.283	198.559	70.987	0.221	12.417	44.244
4290	1.642	8.402	181.895	40.221	0.223	13.666	26.841
4300	0.718	7.426	147.333	58.300	0.248	12.977	14.769
4320	0.275	7.081	203.659	95.451	0.215	7.327	34.979
4350	0.741	6.837	159.673	27.577	0.162	4.095	18.124
4370	1.076	7.080	182.337	69.826	0.128	7.943	47.652
4390	0.062	9.911	210.051	25.056	0.099	1.689	29.917
4420	0.543	6.441	139.332	48.853	0.457	14.642	45.488
4480	0.794	4.770	235.734	39.568	0.226	8.635	28.687
4530	1.859	9.172	181.672	21.707	0.236	6.266	35.903
4540	1.808	11.926	193.511	2.072	6.418	24.633	47.140
4550	1.082	2.714	185.395	35.309	0.287	27.027	31.146
4570	1.368	8.165	171.807	45.279	0.686	11.689	37.404
4620	0.770	5.526	156.604	91.620	0.303	11.609	42.997
4650	0.826	10.173	169.299	26.366	0.474	11.987	31.649
4690	0.759	6.276	120.722	39.838	0.320	13.422	40.005
4710	1.282	10.352	175.543	19.953	0.276	22.672	32.810
4740	1.577	5.795	212.710	60.748	0.179	11.776	45.125
4770	0.367	5.507	161.682	54.982	0.116	5.352	28.883
4780	0.952	9.919	156.710	33.039	0.368	14.093	41.173
4730	1.719	5.547	171.180	73.307	0.192	6.868	32.887
4400	1.721	7.179	216.889	23.330	0.047	1.417	9.321
208645	1.721	8.031	185.046	33.461	0.148	14.497	37.922
209171	0.432	6.948	154.832	57.853	0.232	9.191	43.794
209601	0.439	8.838	137.897	29.340	0.243	5.280	48.730
209742	1.761	11.784	99.975	32.864	0.312	11.358	39.375
209734	1.192	29.183	67.015	34.417	0.456	18.761	20.565
208629	0.963	12.396	147.234	32.129	0.251	2.951	40.769
208637	1.049	8.691	214.397	31.530	0.057	4.947	35.525

Tab. 6.36: Parameter values for calibration variant semi-distributed 91 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4470	0.934	2.265	1.159	-1.713	-0.269	0.691	241.744	3.465
4560	1.068	1.413	2.489	-1.903	-1.592	0.948	235.041	5.397
4610	1.288	2.102	2.814	-0.369	-0.472	0.345	403.796	2.294
4660	1.045	0.591	1.078	-2.621	-1.845	0.598	343.456	9.537
4700	1.071	2.791	2.221	-1.910	0.008	0.866	252.265	4.782
4720	1.217	1.142	1.581	-2.832	-1.097	0.899	289.296	5.327
4760	0.930	4.210	1.433	-0.427	0.566	0.827	243.304	5.414
4290	0.908	2.159	2.895	-2.676	-0.125	0.826	246.934	4.521
4300	0.926	1.554	2.386	-2.402	-0.588	0.934	209.351	5.353
4320	0.907	3.642	2.872	-1.876	0.676	0.735	221.446	4.411
4350	1.001	2.897	1.289	-1.146	0.428	0.733	219.420	3.850

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Tab. 6.36: Parameter values for calibration variant semi-distributed 91 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4370	1.002	1.325	1.582	-1.512	-0.905	0.606	234.323	3.379
4390	1.202	2.214	1.624	-0.257	-0.044	0.897	316.026	6.021
4420	0.926	2.005	2.591	-2.072	-1.074	0.901	246.037	4.262
4480	0.913	0.973	1.528	-0.964	-1.892	0.838	236.203	4.789
4530	0.961	1.175	2.661	-2.319	-1.452	0.789	360.508	3.795
4540	1.178	3.238	1.459	0.716	-0.110	0.632	260.763	1.937
4550	0.901	2.832	2.829	0.864	-0.039	0.945	371.504	8.901
4570	1.090	4.240	1.359	-0.887	0.670	0.486	275.319	1.893
4620	1.042	3.594	1.437	-1.536	0.037	0.576	249.227	2.861
4650	0.962	2.942	1.434	-2.225	0.517	0.855	267.638	4.243
4690	0.984	2.398	1.146	-2.638	0.141	0.996	255.351	5.872
4710	0.981	1.694	1.650	-1.599	-0.756	0.754	217.302	3.649
4740	0.909	2.671	2.442	-2.629	0.383	0.844	236.418	4.516
4770	1.393	3.857	1.245	-1.880	0.657	0.611	311.734	3.617
4780	1.352	1.512	1.372	-2.089	-1.300	0.733	268.587	3.841
4730	1.268	1.546	2.831	-0.560	-0.960	0.785	205.791	3.578
4400	1.157	1.271	1.489	0.203	-1.376	0.746	309.641	5.011
208645	1.024	2.710	2.241	-2.753	0.200	0.556	226.514	3.042
209171	1.150	2.082	1.016	-2.967	-0.146	0.790	231.477	4.346
209601	0.950	1.329	2.422	-2.365	-1.017	0.893	245.941	5.568
208629	1.231	2.254	1.058	-2.949	-0.310	0.779	235.785	3.608
208637	1.020	2.210	1.883	0.697	1.022	0.473	429.776	2.792

Tab. 6.37: Parameter values for calibration variant semi-distributed 91 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4470	0.918	7.580	237.620	71.851	0.189	16.230	46.353
4560	0.910	5.460	143.377	94.415	0.149	5.662	35.953
4610	1.726	5.287	246.313	38.633	0.138	6.024	27.691
4660	1.258	7.149	198.273	81.437	0.149	5.286	37.965
4700	0.786	7.539	241.424	62.481	0.298	8.557	48.067
4720	0.788	5.199	227.156	91.364	0.081	10.457	32.963
4760	1.324	6.755	240.898	97.552	0.198	3.810	41.361
4290	1.521	8.072	235.366	53.328	0.178	14.345	37.783
4300	1.372	7.490	236.251	69.157	0.230	3.612	31.908
4320	1.340	7.428	234.953	34.844	0.117	6.217	45.505
4350	1.225	8.591	241.992	74.725	0.154	7.413	30.334
4370	1.476	6.111	218.130	99.610	0.044	7.463	47.262
4390	0.028	7.384	234.720	85.095	0.033	1.768	26.025
4420	0.794	8.457	216.886	28.594	0.406	1.203	11.328
4480	1.167	6.700	233.597	86.777	0.343	14.936	40.468
4530	1.571	15.973	194.699	20.829	0.525	24.720	14.224
4540	0.998	11.117	235.042	92.607	1.531	10.288	17.719
4550	1.181	2.633	243.464	69.471	0.257	1.195	5.130
4570	1.231	9.575	237.922	56.346	0.542	12.975	35.595
4620	0.306	5.898	225.900	78.701	0.273	18.917	42.887
4650	0.079	11.318	230.068	51.900	0.448	10.848	45.521
4690	0.719	11.130	236.864	77.098	0.276	8.460	45.108
4710	0.204	6.318	246.216	10.338	0.278	11.030	26.394
4740	0.915	8.612	230.583	73.489	0.133	12.335	33.173
4770	0.414	4.030	211.545	65.078	0.108	9.580	13.140

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Tab. 6.37: Parameter values for calibration variant semi-distributed 91 (2/2) (Continuation)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4780	0.603	9.689	231.243	76.903	0.398	8.025	38.483
4730	1.164	9.291	227.701	61.556	0.201	6.846	13.623
4400	0.404	7.181	204.932	93.660	0.044	7.041	21.599
208645	1.834	6.390	233.073	76.114	0.066	5.825	32.593
209171	1.357	5.957	237.986	32.296	0.174	1.015	49.393
209601	1.655	10.275	232.918	73.208	0.243	14.537	48.279
208629	1.495	7.011	214.811	69.756	0.178	11.560	40.348
208637	0.880	2.034	233.387	99.151	0.099	10.192	21.801

Tab. 6.38: Parameter values for calibration variant semi-distributed 86 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4470	1.040	2.482	1.326	-2.931	0.556	0.756	255.198	3.848
4560	1.242	3.716	1.375	-2.739	0.801	0.840	238.982	4.077
4610	1.388	3.870	2.125	-2.763	1.423	0.407	475.760	2.381
4660	0.919	2.750	2.669	0.887	-1.006	0.674	376.103	8.229
4700	0.978	3.850	2.241	-2.813	1.051	0.984	259.360	6.669
4720	0.936	2.228	2.810	0.940	-0.800	0.900	256.080	5.057
4760	1.392	1.872	1.235	-0.757	-0.757	0.764	316.600	4.800
4290	1.020	1.856	2.892	-2.632	-0.689	0.897	264.453	5.750
4300	1.337	3.413	1.002	0.096	-0.122	0.786	271.236	3.748
4320	1.264	3.568	1.304	-0.177	-0.213	0.668	344.205	3.643
4350	1.274	4.128	1.329	-1.825	0.601	0.878	266.894	4.804
4370	1.195	4.397	1.464	-2.230	0.148	0.748	253.942	4.164
4390	1.496	3.171	1.500	-0.196	0.820	0.701	308.323	4.387
4420	1.056	2.204	1.192	-1.145	-1.080	0.950	309.107	4.770
4480	0.978	2.254	1.973	-2.762	0.114	0.851	275.685	4.566
4530	1.201	4.703	1.025	-1.461	0.030	0.690	379.304	3.468
4540	1.492	2.738	1.825	-2.624	-0.702	0.402	247.164	1.428
4550	0.903	0.956	2.796	-0.298	-1.994	0.908	341.192	8.045
4570	1.189	3.072	1.584	-2.419	0.379	0.617	276.185	2.423
4620	0.952	1.816	1.396	-1.892	-0.930	0.755	264.343	3.830
4650	1.007	3.143	2.300	-2.912	-0.550	0.841	277.910	4.640
4690	0.931	3.118	1.367	-2.668	0.256	0.998	250.930	7.476
4710	0.900	2.246	2.205	-0.912	0.028	0.939	224.003	5.464
4740	1.095	3.460	1.651	-2.289	0.666	0.808	242.987	4.530
4770	1.432	3.165	2.231	0.316	-0.246	0.734	351.699	4.326
4780	1.367	4.691	2.437	-2.274	0.351	0.830	335.840	4.628
4730	1.437	2.068	1.018	-0.333	-0.727	0.878	259.595	4.321
4400	1.464	4.103	1.091	0.914	0.176	0.655	321.889	4.306
208645	1.213	4.932	2.648	-2.296	0.165	0.471	258.242	2.439
209171	1.178	3.949	1.370	-2.183	0.488	0.986	285.175	6.358
208629	1.422	4.056	1.427	-2.341	-0.343	0.811	276.849	3.990
208637	1.487	2.593	2.298	0.384	1.115	0.391	519.627	2.507

Tab. 6.39: Parameter values for calibration variant semi-distributed 86 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4470	0.417	7.817	181.322	87.238	0.210	0.957	37.442
4560	0.393	6.044	212.756	58.268	0.130	12.319	20.837
4610	0.194	6.061	149.042	66.338	0.060	3.344	17.267
4660	1.435	5.695	217.299	38.622	0.130	23.783	8.959
4700	0.123	7.716	224.011	33.954	0.293	19.186	37.933
4720	1.956	5.168	201.634	16.300	0.095	8.149	35.692
4760	0.635	5.826	223.491	66.629	0.185	13.228	14.842
4290	1.897	7.892	198.977	67.141	0.212	5.199	1.414
4300	1.782	8.799	184.151	29.183	0.176	0.353	17.685
4320	1.404	4.578	153.160	64.231	0.092	9.147	9.658
4350	0.210	5.981	200.458	69.318	0.132	2.079	27.054
4370	0.489	7.758	185.270	63.168	0.079	10.777	44.032
4390	0.340	5.423	245.228	33.639	0.061	2.930	29.405
4420	0.197	7.624	184.634	79.914	0.323	20.841	33.154
4480	1.686	7.652	221.501	86.475	0.176	11.659	24.064
4530	1.700	27.562	204.042	16.599	0.690	22.595	3.690
4540	1.268	10.886	237.868	56.486	1.293	11.876	45.808
4550	1.593	3.425	206.976	24.498	0.141	9.085	24.797
4570	0.864	8.064	211.989	81.851	0.457	2.919	20.899
4620	0.331	8.901	211.115	86.976	0.226	3.225	38.104
4650	0.773	10.714	196.525	62.167	0.393	11.631	28.558
4690	0.585	14.819	212.549	86.673	0.295	8.735	35.097
4710	0.384	6.571	235.287	97.899	0.356	11.509	46.575
4740	1.003	7.847	230.835	57.681	0.175	10.877	19.691
4770	0.881	6.061	155.611	23.411	0.127	11.930	30.180
4780	0.794	8.207	191.495	54.941	0.295	9.705	48.449
4730	0.304	7.309	238.886	57.598	0.189	1.543	18.265
4400	1.882	3.555	248.572	12.349	0.128	17.487	6.857
208645	1.858	6.902	194.902	81.025	0.072	7.458	31.992
209171	1.334	8.226	174.645	50.514	0.111	4.226	14.534
208629	0.212	7.708	157.010	32.293	0.208	7.314	35.606
208637	1.067	3.063	234.858	30.183	0.197	11.605	4.867

Tab. 6.40: Parameter values for calibration variant snow 01-11 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4440	0.902	2.759	2.834	-0.066	-0.872	0.860	140.091	4.291
4451	0.900	2.028	2.981	-2.960	-0.765	0.908	219.241	5.526
4460	0.909	2.104	1.713	-0.855	-0.962	0.995	234.031	6.015
4470	0.905	2.065	2.110	-1.361	-0.729	0.950	220.282	5.657
4560	1.005	4.532	2.644	-2.929	0.714	0.905	182.833	4.969
4566	0.915	2.351	2.685	-1.478	-0.292	0.305	202.583	1.318
4580	0.908	3.777	1.802	-0.997	1.165	0.492	374.409	2.498
4610	1.366	4.339	2.765	-1.392	0.009	0.416	493.624	2.608
4630	0.901	3.107	1.343	-2.894	0.789	0.964	223.576	5.053
4660	0.900	4.939	2.998	0.985	0.650	0.696	437.110	8.255
4700	0.903	2.931	2.871	-1.169	-0.263	0.986	226.941	6.130
4720	0.960	2.971	1.226	-0.426	-0.067	0.974	246.330	7.577
4760	0.977	2.307	2.966	-2.483	0.233	0.841	233.333	4.630
4290	0.906	3.083	2.872	-2.937	0.554	0.931	249.297	5.941

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Tab. 6.40: Parameter values for calibration variant snow 01-11 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4300	0.939	3.366	2.242	-1.670	1.268	0.995	172.764	5.930
4320	0.918	1.983	2.624	0.806	-0.290	0.826	227.461	4.532
4350	0.906	2.819	2.970	-1.374	0.785	0.950	169.671	5.504
4370	0.906	3.061	1.942	-0.437	0.664	0.825	205.340	4.474
4390	0.904	2.030	2.652	-2.901	0.640	0.906	215.183	5.232
4410	0.908	4.415	1.571	-2.787	0.013	0.995	190.123	4.970
4420	0.919	3.346	2.647	-2.389	-0.440	0.974	183.539	5.503
4480	0.901	2.967	2.759	-0.347	-0.799	0.890	248.412	5.197
4520	1.077	2.178	2.020	-2.443	-0.684	0.243	143.886	0.681
4530	1.007	2.560	2.640	-2.313	-0.769	0.531	200.235	2.505
4540	0.911	4.841	1.516	-2.830	0.821	0.649	160.929	1.942
4550	0.900	2.203	2.820	-2.996	-0.908	0.572	201.082	3.394
4570	0.905	4.958	2.872	-2.486	0.784	0.468	191.496	1.843
4620	0.900	3.914	2.827	-2.996	0.386	0.826	266.577	4.794
4650	0.901	4.130	1.646	-2.849	1.371	0.865	256.631	4.657
4690	0.901	4.720	2.048	-2.990	1.514	0.992	231.574	6.734
4710	0.953	3.116	2.882	-1.134	-0.196	0.971	218.047	5.956
4740	0.900	4.985	2.889	-2.785	1.147	0.942	230.084	6.460
4770	0.993	2.102	2.218	-2.952	0.484	0.840	249.898	5.094
4780	0.912	2.720	2.734	-2.966	0.624	0.955	222.416	5.897
4860	0.901	4.334	2.339	-1.216	0.840	0.379	401.565	2.002
4730	1.122	4.713	2.562	-2.990	1.082	0.984	212.436	5.851
4400	0.993	4.188	1.019	-2.986	1.980	0.753	246.137	4.488
208645	0.901	2.952	2.625	-1.228	0.690	0.912	197.106	5.449
209171	0.900	2.727	2.946	-1.169	0.543	0.886	179.978	4.887
209759	1.458	2.544	1.176	-2.912	0.197	0.851	222.834	5.200
209601	0.909	2.950	2.870	-2.938	0.503	0.963	223.640	6.499
209742	1.102	3.342	2.319	-1.235	0.880	0.930	119.404	4.028
209734	0.901	2.864	2.991	-1.888	0.602	0.559	38.233	4.550
208629	0.910	2.739	1.841	-0.974	0.671	0.977	155.609	5.748
208637	1.288	4.392	2.805	0.317	0.784	0.488	585.492	2.900
209510	1.039	4.992	2.085	0.476	1.523	0.559	362.008	3.055
209320	1.035	4.788	2.642	-0.206	1.551	0.570	368.220	3.061
208611	1.173	3.199	2.639	-2.492	0.859	0.987	109.455	4.751
209775	1.424	4.260	2.647	-2.401	1.497	0.315	108.498	1.576

Tab. 6.41: Parameter values for calibration variant snow 01-11 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4440	1.181	12.844	168.269	54.828	0.391	17.980	47.503
4451	0.985	10.305	193.120	37.034	0.358	13.393	46.104
4460	1.242	8.911	201.647	60.071	0.269	12.608	43.880
4470	0.926	10.696	173.751	38.069	0.248	5.580	21.133
4560	0.991	7.445	240.190	50.443	0.181	19.166	25.194
4566	0.753	19.484	215.192	18.005	0.249	15.640	21.449
4580	1.898	3.981	241.018	47.136	0.100	3.920	0.119
4610	1.067	5.706	215.702	35.478	0.156	4.312	32.829
4630	1.976	19.274	153.978	33.523	0.586	15.766	34.754
4660	1.295	9.105	139.013	89.233	0.139	29.252	29.304
4700	0.340	14.668	249.682	24.033	0.324	20.982	41.899
4720	0.886	6.492	248.887	38.641	0.149	9.099	34.784

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Tab. 6.41: Parameter values for calibration variant snow 01-11 (2/2) (Continuation)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4760	0.372	9.773	242.014	9.860	0.153	7.446	48.405
4290	0.520	9.060	248.715	62.047	0.191	9.866	48.894
4300	0.361	11.290	171.111	23.426	0.257	9.137	35.549
4320	0.635	3.922	237.203	8.514	0.176	14.624	4.480
4350	1.951	12.679	202.298	23.918	0.190	9.709	49.768
4370	1.245	8.855	239.119	30.179	0.133	4.861	14.403
4390	1.953	10.646	161.929	14.696	0.127	0.937	19.338
4410	1.013	14.260	247.955	87.566	0.485	18.656	16.495
4420	1.338	14.091	154.804	53.908	0.501	23.844	47.590
4480	1.073	9.111	218.830	48.382	0.254	13.134	47.801
4520	1.946	28.323	199.626	41.150	2.413	0.150	33.440
4530	0.921	8.720	240.840	16.018	0.112	6.449	25.456
4540	1.426	22.859	181.946	40.889	1.093	20.638	33.317
4550	1.095	4.376	228.822	12.172	0.021	16.565	28.031
4570	0.968	11.211	180.013	32.469	0.578	12.549	31.594
4620	1.061	9.009	203.580	33.697	0.269	11.717	47.180
4650	0.753	9.856	162.839	52.685	0.537	13.806	43.332
4690	0.328	12.439	180.142	26.929	0.368	10.883	32.078
4710	0.425	13.212	244.273	28.462	0.314	26.210	49.856
4740	1.423	8.355	246.274	42.289	0.161	8.508	42.830
4770	1.154	9.772	248.790	11.347	0.081	4.392	25.357
4780	0.500	10.854	180.033	23.732	0.210	6.385	29.549
4860	1.405	2.853	167.047	8.371	0.141	10.139	1.924
4730	0.404	8.312	226.342	36.781	0.203	8.654	34.919
4400	0.457	7.791	249.687	12.115	0.053	2.878	21.683
208645	0.345	9.718	212.047	25.060	0.182	8.499	41.397
209171	0.846	11.757	235.678	18.415	0.200	11.803	49.574
209759	0.868	6.399	215.399	12.144	0.248	11.274	42.294
209601	0.278	12.078	224.069	16.442	0.183	10.053	48.706
209742	0.740	7.097	105.262	47.355	0.270	15.689	5.073
209734	0.452	25.610	72.682	58.253	0.316	26.320	23.153
208629	1.999	15.207	166.353	24.618	0.216	8.772	25.173
208637	0.982	2.036	248.984	2.916	0.111	22.044	15.086
209510	1.414	2.045	241.981	1.033	0.294	23.269	7.664
209320	0.788	2.112	249.912	2.125	0.280	20.838	6.947
208611	0.948	8.229	72.862	34.383	0.201	8.781	48.613
209775	0.996	26.070	248.839	12.181	0.310	9.453	24.440

Tab. 6.42: Parameter values for calibration variant snow 96 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4440	0.910	2.065	2.555	0.717	-1.123	0.818	176.771	4.282
4451	0.907	2.048	2.989	-1.236	-0.772	0.456	158.071	2.277
4460	0.920	1.809	1.063	-0.346	-0.949	0.807	200.279	3.858
4470	0.903	2.070	1.823	-1.102	-0.709	0.737	211.221	3.473
4560	0.987	4.006	2.445	-2.007	0.638	0.892	181.989	4.641
4566	0.900	4.270	2.981	0.981	0.433	0.817	261.804	2.968
4580	0.909	3.381	1.189	-1.169	1.112	0.550	290.244	3.077
4610	1.152	3.836	1.109	-2.888	0.847	0.531	383.574	3.110
4630	0.902	3.828	1.657	-2.802	1.042	0.815	176.878	3.248
4660	0.900	3.023	2.947	0.945	-0.526	0.498	371.528	5.116

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Tab. 6.42: Parameter values for calibration variant snow 96 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4700	0.904	1.525	1.015	-0.093	-1.026	0.733	185.112	3.335
4720	0.988	3.228	1.020	0.592	-0.268	0.883	217.488	5.296
4760	0.909	2.715	2.987	-2.650	0.573	0.802	194.638	4.602
4290	0.900	4.937	2.267	-2.986	1.629	0.785	208.040	4.173
4300	0.900	4.926	2.770	-2.969	1.712	0.882	156.747	4.616
4320	0.901	2.795	2.992	0.818	0.112	0.813	209.145	4.719
4350	0.901	3.622	2.988	0.621	0.376	0.802	162.988	4.069
4370	0.900	4.628	2.848	0.324	0.789	0.654	176.741	3.406
4390	0.901	2.963	1.718	-2.956	1.139	0.827	206.801	4.926
4410	0.943	1.623	1.161	-2.888	-0.100	0.656	126.687	2.234
4420	0.901	1.665	2.444	-2.037	-1.124	0.379	108.503	1.595
4480	0.901	1.380	2.905	-0.845	-1.559	0.502	180.716	2.340
4520	0.914	4.455	2.961	-2.713	0.284	0.827	62.843	1.969
4530	0.901	4.310	2.313	-2.682	0.653	0.531	207.354	2.316
4540	0.913	4.993	2.922	-2.612	0.764	0.670	134.138	2.074
4550	0.900	4.771	2.778	0.987	0.057	0.458	210.083	3.039
4570	0.919	4.351	1.686	-1.819	0.886	0.526	221.727	2.052
4620	0.908	4.275	2.496	-2.862	0.867	0.603	252.295	2.885
4650	0.900	3.467	2.885	-2.956	0.511	0.752	209.554	3.192
4690	0.900	3.585	2.922	0.250	-0.064	0.800	178.686	3.547
4710	0.908	1.379	1.068	0.052	-1.051	0.914	213.315	5.549
4740	0.902	1.397	2.865	-0.253	-1.346	0.742	196.985	3.970
4770	0.906	2.264	2.915	-2.364	0.437	0.732	216.985	4.091
4780	0.920	4.245	2.949	0.102	0.185	0.780	189.846	3.926
4860	0.902	2.766	2.120	-1.238	0.311	0.603	359.524	2.954
4730	1.077	1.369	2.875	-0.602	-1.677	0.967	212.106	5.646
4400	0.916	1.703	2.038	-2.926	0.455	0.656	234.028	3.878
208645	0.900	3.862	2.990	0.943	0.390	0.812	191.434	4.499
209171	0.900	2.950	2.998	-2.930	1.091	0.763	171.374	3.666
209601	0.900	4.096	2.716	0.628	0.216	0.837	171.576	4.639
209742	0.901	3.125	1.815	-2.772	1.904	0.997	120.786	4.977
209734	0.901	4.735	1.630	-2.968	1.897	0.015	27.567	1.482
208629	0.901	4.845	2.284	-2.912	1.713	0.957	163.220	5.349
208637	0.995	3.313	2.081	-0.198	0.948	0.370	456.330	2.397
209510	0.994	4.869	1.646	0.936	1.112	0.409	343.352	2.216
209320	1.063	4.840	1.559	-0.191	1.364	0.448	358.606	2.418
208611	0.900	2.595	2.977	-2.947	1.258	0.997	80.049	4.642

Tab. 6.43: Parameter values for calibration variant snow 96 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4440	0.765	12.478	249.610	65.057	0.284	22.118	23.896
4451	1.930	8.838	187.801	70.638	0.270	11.577	32.279
4460	0.811	10.145	164.342	36.843	0.238	16.899	43.568
4470	1.977	8.264	175.763	55.255	0.218	13.069	30.116
4560	0.911	5.588	116.433	71.942	0.213	5.900	30.561
4566	1.038	19.012	241.994	6.739	0.308	15.456	1.402
4580	0.908	6.412	223.083	9.278	0.127	6.042	0.536
4610	0.601	6.806	204.932	8.549	0.122	8.189	49.579
4630	0.905	14.335	123.637	42.221	0.663	20.385	41.971
4660	0.612	6.329	113.527	20.218	0.082	13.694	49.760

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Tab. 6.43: Parameter values for calibration variant snow 96 (2/2) (Continuation)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4700	1.844	5.464	178.402	29.874	0.348	15.702	42.390
4720	1.045	6.177	196.996	72.332	0.162	12.296	45.126
4760	1.432	6.629	200.851	48.328	0.222	10.169	45.975
4290	0.932	8.448	184.106	31.413	0.232	8.130	12.834
4300	1.031	10.764	155.809	24.395	0.234	10.196	40.108
4320	0.993	6.501	218.060	24.207	0.187	13.109	47.921
4350	0.917	9.185	167.051	29.475	0.195	8.798	45.885
4370	1.083	8.378	190.884	28.981	0.140	6.178	37.717
4390	1.220	9.785	151.089	46.518	0.103	6.297	32.306
4410	1.825	7.433	101.031	50.357	0.804	25.459	39.339
4420	1.120	7.658	126.831	38.998	0.534	18.497	39.438
4480	0.813	5.535	172.413	40.208	0.259	15.033	40.472
4520	0.222	22.895	239.542	93.785	6.455	20.607	33.004
4530	0.882	10.004	145.578	25.704	0.309	13.646	43.731
4540	0.413	16.850	180.960	79.046	1.894	29.406	47.304
4550	0.542	2.481	174.113	45.517	0.342	29.040	43.793
4570	0.810	8.927	185.153	56.178	0.580	14.455	40.317
4620	1.569	6.493	199.431	47.454	0.250	14.047	49.298
4650	1.275	11.097	143.648	32.614	0.502	16.456	38.718
4690	1.104	9.290	133.992	45.829	0.377	13.545	46.938
4710	1.068	8.601	175.408	17.831	0.291	19.947	35.830
4740	0.674	5.817	197.098	32.104	0.166	11.873	48.263
4770	1.166	7.171	188.267	31.346	0.099	5.501	25.228
4780	1.106	9.240	147.136	59.464	0.332	9.917	33.351
4860	1.169	4.877	157.985	7.714	0.167	6.779	47.162
4730	0.413	8.128	193.891	16.017	0.197	6.501	22.340
4400	1.862	7.495	220.263	62.817	0.036	3.917	39.349
208645	0.915	8.230	240.925	28.110	0.146	7.650	48.285
209171	0.985	7.965	184.296	27.618	0.191	9.264	46.898
209601	1.669	11.763	155.069	34.432	0.249	11.212	49.791
209742	1.491	13.075	115.956	17.113	0.251	10.459	18.856
209734	1.255	28.058	59.001	27.892	0.319	7.589	7.750
208629	1.176	11.111	128.797	30.259	0.255	15.510	48.438
208637	1.403	2.141	201.245	7.445	0.091	21.658	17.792
209510	0.323	2.282	204.651	86.743	0.243	21.624	7.934
209320	0.286	2.187	201.752	76.429	0.226	21.950	7.863
208611	0.831	13.270	64.741	16.247	0.183	16.136	24.524

Tab. 6.44: Parameter values for calibration variant distributed 96 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4300	0.965	3.107	2.584	-2.614	1.808	0.918	211.491	6.581
4350	1.072	4.051	2.087	-0.750	0.222	0.910	307.915	5.294
4370	1.205	2.145	1.522	0.230	-0.662	0.478	416.435	16.382
4420	0.973	4.753	1.704	-2.175	-1.761	0.262	139.667	1.583
4480	0.911	3.356	2.889	-1.860	1.700	0.801	426.177	7.576
4540	1.028	2.530	1.095	-2.518	1.490	0.975	278.274	17.132
4570	1.166	3.415	1.954	0.711	-0.033	0.617	474.267	5.009
4620	1.069	0.327	1.977	-1.120	-0.951	0.309	365.327	15.411
4650	0.955	4.810	2.947	-1.908	0.889	0.600	210.278	2.191
4690	0.918	2.672	2.968	0.313	-0.434	0.804	129.250	3.408

Continued on next page

Tab. 6.44: Parameter values for calibration variant distributed 96 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T _R [°C]	T _S [°C]	T _M [°C]	LP [-]	FC [mm]	β [-]
4710	0.919	4.595	1.755	-0.164	-1.489	0.760	142.108	4.579
4740	0.938	4.692	2.187	-2.291	-1.333	0.735	276.040	4.661
4770	0.919	1.203	1.237	-1.858	-0.066	0.702	277.847	4.087
4780	0.916	4.720	1.735	-2.131	-0.279	0.124	320.560	0.733
4730	1.271	4.674	2.334	-2.840	0.660	0.506	109.862	2.060
4470	0.929	2.669	1.927	-2.232	-1.964	0.048	85.708	0.742
209171	1.084	3.488	1.437	-0.923	1.122	0.464	546.986	4.287
209601	0.947	2.939	2.721	-1.137	-1.984	0.997	57.788	12.664
209742	0.923	2.217	2.945	-1.538	0.549	0.995	180.216	8.034
208629	1.334	3.075	1.252	-2.706	-0.173	0.733	37.046	4.889
208637	1.247	1.764	1.422	-2.484	1.414	0.365	594.093	2.626

Tab. 6.45: Parameter values for calibration variant distributed 96 (2/2)

ID	k ₀ [days]	k ₁ [days]	k ₂ [days]	L _{UZ} [mm]	C _{perc} [mm/day]	B _{MAX} [days]	C _{ROUTE} [days ² /mm]
4300	0.255	6.773	220.239	76.140	0.287	20.732	14.641
4350	1.862	5.042	228.017	7.398	0.211	0.285	30.386
4370	1.331	20.961	101.011	87.574	2.407	14.928	43.085
4420	0.322	3.960	146.218	60.405	0.424	11.093	18.519
4480	1.984	4.239	134.785	46.370	0.098	18.428	38.507
4540	0.602	12.814	173.773	24.946	0.401	14.644	34.665
4570	1.226	5.910	125.540	86.907	0.099	7.497	13.831
4620	1.871	27.355	48.085	97.263	5.548	1.803	0.552
4650	0.265	6.147	155.292	73.899	0.447	4.335	12.853
4690	1.053	12.022	117.936	56.303	0.270	6.615	30.260
4710	0.677	10.366	105.728	89.660	0.095	16.072	25.087
4740	1.031	7.109	133.271	62.371	0.010	13.791	43.356
4770	1.715	8.350	78.670	80.224	0.019	3.316	18.405
4780	1.423	29.373	108.549	6.047	6.507	6.164	2.528
4730	1.335	17.454	168.049	50.230	0.027	17.475	37.281
4470	1.546	4.823	30.269	86.314	7.068	6.807	19.417
209171	0.989	17.177	110.748	73.773	1.501	18.683	44.225
209601	1.267	26.074	30.669	80.380	0.592	6.355	38.744
209742	1.343	10.461	160.667	46.773	0.315	12.350	25.231
208629	1.300	8.894	43.143	45.562	1.427	0.333	21.376
208637	1.052	3.952	135.613	30.296	0.024	4.576	41.725

Tab. 6.46: Parameter values for calibration variant distributed 91 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T _R [°C]	T _S [°C]	T _M [°C]	LP [-]	FC [mm]	β [-]
4300	0.982	2.603	2.664	-1.212	-1.333	0.617	79.530	2.683
4350	1.275	2.152	2.444	-1.478	0.561	0.036	217.131	13.775
4370	1.484	3.527	1.942	0.078	0.259	0.173	282.922	12.467
4420	0.912	2.211	1.775	0.073	-1.116	0.705	224.312	2.690
4480	0.900	2.241	1.830	-2.029	-0.723	0.817	259.664	6.158
4540	1.000	1.832	1.661	-2.131	-0.055	0.795	218.027	6.917
4570	1.368	0.906	1.142	-1.963	0.866	0.685	428.300	6.882

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Tab. 6.46: Parameter values for calibration variant distributed 91 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4620	1.361	4.430	2.564	-1.613	1.932	0.742	319.235	14.244
4650	1.259	1.737	1.526	-2.696	-0.512	0.773	323.942	3.368
4690	1.166	0.933	2.124	-2.346	-1.935	0.971	268.900	6.080
4710	0.991	4.011	2.077	-1.975	-0.603	0.828	233.607	13.220
4740	1.061	1.625	1.691	-2.659	-0.400	0.981	351.182	8.139
4770	1.236	1.929	1.568	-1.097	1.163	0.546	235.730	3.144
4780	1.336	3.211	1.863	-1.958	-0.790	0.877	475.344	2.135
4730	1.365	0.810	1.996	-1.997	0.105	0.919	152.366	3.857
4470	0.933	3.430	2.645	-0.068	1.313	0.714	274.562	2.917
209171	1.395	2.038	2.004	-0.126	-1.239	0.833	370.031	18.336
208629	1.421	2.994	1.047	-1.790	0.036	0.797	259.739	3.701
208637	1.153	2.034	1.857	-1.567	1.049	0.736	580.522	5.178

Tab. 6.47: Parameter values for calibration variant distributed 91 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4300	0.965	16.194	219.350	92.645	0.172	1.950	41.563
4350	1.899	18.767	159.215	12.627	5.507	28.787	10.400
4370	0.760	10.100	66.197	70.101	6.732	27.340	28.965
4420	0.778	5.134	213.189	52.865	0.405	7.346	46.775
4480	1.691	8.271	158.816	29.292	0.010	6.492	21.084
4540	0.455	3.718	211.709	27.075	0.075	2.903	1.163
4570	0.888	14.618	233.022	27.560	0.364	5.530	44.384
4620	0.430	12.746	88.876	17.727	1.239	4.817	3.335
4650	1.951	9.094	210.292	43.791	0.348	1.081	29.434
4690	0.879	10.056	194.049	44.621	0.136	8.190	35.768
4710	1.349	4.916	44.822	53.102	0.028	11.858	4.600
4740	1.091	7.040	222.694	98.613	0.248	3.322	44.004
4770	0.319	5.263	101.332	40.087	0.002	3.204	39.775
4780	0.079	27.327	245.942	65.351	4.611	22.609	18.161
4730	0.116	12.173	200.548	68.702	0.203	13.486	34.292
4470	0.773	2.979	181.868	22.321	0.412	15.369	42.916
209171	1.166	7.261	77.524	18.092	6.878	1.086	34.307
208629	0.705	5.958	208.489	53.473	0.209	3.275	29.299
208637	1.313	4.570	244.415	79.086	0.168	4.588	35.955

Tab. 6.48: Parameter values for calibration variant distributed 86 (1/2)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4300	1.127	1.241	1.870	0.107	1.010	0.993	67.144	17.368
4350	1.493	4.663	1.386	-1.823	1.231	0.950	277.795	10.010
4370	1.118	2.978	2.771	0.443	-1.116	0.928	355.730	13.708
4420	1.047	1.599	1.026	-2.897	-1.268	0.830	322.020	3.998
4480	1.268	4.510	1.985	0.960	0.607	0.567	366.696	4.353
4540	0.970	3.335	1.695	-2.294	-0.551	0.932	340.119	14.435
4570	1.301	1.945	1.510	-0.458	1.155	0.516	550.100	3.487
4620	1.413	2.319	1.938	0.261	-1.366	0.701	313.063	12.585

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Tab. 6.48: Parameter values for calibration variant distributed 86 (1/2) (Continuation)

ID	SCF [-]	DDF [mm/°C/days]	T_R [°C]	T_S [°C]	T_M [°C]	LP [-]	FC [mm]	β [-]
4650	0.986	3.728	1.307	-0.427	0.276	0.873	246.221	4.250
4690	1.057	2.720	1.632	-1.955	-0.685	0.933	242.929	5.928
4710	1.064	3.526	1.913	0.483	-0.158	0.007	545.111	0.315
4740	1.464	3.390	1.315	0.344	0.314	0.747	352.757	5.787
4770	1.484	3.410	2.223	0.964	0.541	0.498	276.875	2.703
4780	1.484	2.749	1.476	-0.061	1.765	0.976	104.991	6.287
4730	1.471	2.928	1.854	0.190	1.085	0.966	169.554	4.959
4470	1.008	3.573	2.651	0.104	-1.697	0.124	159.228	1.523
209171	1.199	1.705	1.059	0.464	-0.155	0.431	207.136	6.040
208629	1.435	3.684	1.187	-2.687	-0.546	0.937	223.158	6.264
208637	1.494	4.144	2.234	0.699	-0.065	0.726	375.532	6.165

Tab. 6.49: Parameter values for calibration variant distributed 86 (2/2)

ID	k_0 [days]	k_1 [days]	k_2 [days]	L_{UZ} [mm]	C_{perc} [mm/day]	B_{MAX} [days]	C_{ROUTE} [days ² /mm]
4300	1.906	14.318	232.972	1.814	1.723	6.995	29.410
4350	0.826	29.419	33.754	28.514	6.601	12.992	3.921
4370	1.132	9.402	74.495	84.212	4.099	23.877	22.649
4420	0.814	9.391	188.365	85.081	0.250	9.738	48.901
4480	0.395	3.897	231.979	64.396	0.248	12.951	23.149
4540	1.213	3.734	195.171	88.877	0.008	3.317	7.317
4570	0.333	5.406	149.820	79.328	0.007	16.854	17.539
4620	0.551	2.678	45.161	86.723	3.667	3.716	45.262
4650	0.866	8.487	175.329	59.670	0.377	9.625	28.825
4690	0.918	14.134	219.926	38.626	0.171	1.611	31.045
4710	0.268	7.045	196.619	32.406	0.262	5.334	16.999
4740	1.992	11.125	194.373	90.968	0.036	0.513	22.492
4770	1.600	6.168	172.078	97.937	0.009	1.545	35.840
4780	1.608	6.356	210.011	13.446	4.977	12.880	26.141
4730	0.887	8.826	206.714	87.987	0.273	28.012	14.726
4470	1.324	12.676	193.204	50.399	0.228	9.805	24.777
209171	0.652	7.771	130.525	59.773	3.493	18.122	40.307
208629	1.307	10.427	156.789	29.358	0.173	7.141	36.865
208637	0.892	2.325	236.415	44.844	0.539	0.889	37.219

6.3 Hydrological projections

6.3.1 Comparison of seasonal data

Tab. 6.50: Changes in discharge for seasonal runoff compared to 30 years historical period [%]

Variant	1	2	3	4	5	6	7	8	9	10	11	12
CMCC 1 lumped 86 126	26.41	14.01	4.36	-18.39	-23.05	-31.76	-15.24	-21.93	-13.26	-7.66	11.80	3.65
CMCC 1 lumped 91 126	27.92	11.65	7.42	-14.00	-22.67	-31.98	-12.41	-19.85	-11.26	-5.40	14.40	6.84
CMCC 1 lumped 96 126	33.23	15.78	8.91	-13.42	-21.59	-30.39	-10.19	-17.12	-9.09	-4.66	19.90	11.95
CMCC 2 semi 86 126	29.43	8.78	-0.66	-15.30	-22.18	-33.72	-16.87	-22.50	-13.95	-7.15	14.05	7.75
CMCC 2 semi 91 126	31.42	11.89	4.11	-14.26	-22.43	-34.20	-14.27	-20.66	-12.17	-5.05	16.89	9.50
CMCC 2 semi 96 126	37.28	13.35	5.09	-11.89	-21.60	-33.36	-11.20	-17.16	-8.99	-2.25	25.25	16.85
CMCC 3 snow 96 126	37.58	17.78	4.97	-9.54	-19.13	-30.50	-11.07	-16.03	-7.89	-1.63	23.48	17.94
CMCC 3 snow 01 126	33.60	12.94	1.97	-10.09	-20.21	-31.93	-14.03	-17.08	-10.57	-2.56	22.18	15.43
CMCC 4 distributed 86 126	32.74	13.25	0.36	-19.23	-20.93	-30.70	-15.96	-18.51	-13.29	-5.46	17.00	12.62
CMCC 4 distributed 91 126	30.86	12.41	3.40	-19.62	-24.27	-32.75	-14.94	-19.77	-13.00	-5.23	17.15	9.87
CMCC 4 distributed 96 126	28.87	8.67	3.71	-11.12	-21.81	-34.82	-16.04	-16.70	-11.49	0.27	28.41	18.33
EC 1 lumped 86 126	15.67	14.56	-10.83	-26.64	-20.71	-22.59	-8.06	-19.98	-18.53	-18.90	-16.57	-12.86
EC 1 lumped 91 126	16.95	12.01	-6.07	-20.76	-19.74	-22.45	-4.90	-17.67	-16.44	-16.62	-14.41	-9.92
EC 1 lumped 96 126	27.96	21.10	-3.62	-18.94	-16.82	-19.79	-2.03	-13.57	-14.10	-17.60	-12.28	-1.58
EC 2 semi 86 126	12.51	5.57	-15.63	-23.38	-19.60	-23.82	-9.14	-20.43	-19.52	-19.11	-16.73	-12.36
EC 2 semi 91 126	18.25	11.06	-9.81	-21.72	-18.83	-23.62	-5.90	-18.03	-17.30	-16.79	-14.22	-8.59
EC 2 semi 96 126	29.11	16.77	-7.57	-17.87	-16.51	-22.10	-2.32	-13.61	-14.80	-17.30	-11.93	-0.96
EC 3 snow 96 126	33.36	22.44	-5.71	-14.91	-13.82	-19.16	-2.43	-12.21	-12.92	-15.15	-9.29	3.74
EC 3 snow 01 126	24.63	14.69	-9.45	-16.12	-15.41	-20.73	-5.19	-13.58	-15.82	-16.28	-11.63	-3.29
EC 4 distributed 86 126	20.22	9.91	-16.32	-32.29	-22.83	-25.42	-11.76	-18.38	-21.05	-20.92	-15.64	-9.47
EC 4 distributed 91 126	22.30	14.23	-10.98	-30.86	-24.84	-25.60	-9.18	-18.79	-19.82	-19.83	-17.32	-10.31
EC 4 distributed 96 126	24.06	11.33	-4.72	-17.07	-18.62	-24.32	-6.80	-12.42	-17.73	-18.61	-12.78	-4.87
GFDL 1 lumped 86 126	3.88	3.96	8.97	-7.32	-5.97	-3.87	25.71	15.91	15.02	12.66	17.05	-3.75
GFDL 1 lumped 91 126	3.18	1.37	12.66	-1.51	-5.36	-4.40	28.53	17.46	15.53	13.70	18.20	-2.27
GFDL 1 lumped 96 126	6.95	4.66	13.93	-1.21	-4.04	-3.73	28.61	20.84	17.96	15.11	21.06	0.82
GFDL 2 semi 86 126	4.35	-0.82	4.71	-2.43	-3.77	-3.82	27.53	19.22	15.82	14.61	20.45	-0.16
GFDL 2 semi 91 126	6.85	1.94	9.97	-0.78	-3.43	-4.26	30.40	21.02	17.13	16.38	22.67	1.43
GFDL 2 semi 96 126	8.54	2.57	11.06	1.50	-2.77	-4.93	31.35	24.86	20.03	18.85	25.91	3.54
GFDL 3 snow 96 126	10.44	6.67	9.77	3.17	-0.90	-3.24	28.04	23.11	19.75	18.61	24.42	6.02
GFDL 3 snow 01 126	6.93	3.28	8.20	4.08	-0.45	-3.21	27.58	24.76	18.83	20.08	25.94	5.34
GFDL 4 distributed 86 126	6.34	1.96	3.69	-11.81	-6.04	-4.71	23.85	22.44	15.69	13.63	17.74	-0.65
GFDL 4 distributed 91 126	6.32	2.80	8.37	-9.81	-6.80	-3.62	28.65	21.28	17.24	15.58	18.29	-2.40
GFDL 4 distributed 96 126	2.97	-0.17	10.74	2.33	-2.49	-5.37	28.00	29.92	21.57	22.25	23.03	-0.02
MPI 1 lumped 86 126	10.43	5.97	14.29	-5.37	-2.84	3.92	30.75	13.68	8.55	2.82	5.64	-7.82
MPI 1 lumped 91 126	9.53	3.52	17.85	-0.78	-2.07	3.54	33.70	15.44	9.45	3.84	6.25	-6.77

Continued on next page

Tab. 6.50: Changes in discharge for seasonal runoff compared to 30 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
MPI 1 lumped 96 126	13.61	6.73	19.42	-0.94	-1.39	3.63	33.34	19.39	12.43	3.70	6.29	-4.26
MPI 2 semi 86 126	10.29	1.38	10.09	-1.24	-0.41	4.51	33.28	16.67	9.35	4.38	7.74	-5.58
MPI 2 semi 91 126	12.86	3.40	14.98	0.21	-0.11	4.02	36.10	18.34	10.52	5.63	8.75	-4.30
MPI 2 semi 96 126	15.28	4.54	16.13	1.19	0.09	3.33	37.23	23.15	14.25	6.06	8.46	-2.88
MPI 3 snow 96 126	17.00	8.36	14.79	3.30	1.72	4.64	33.40	21.70	14.01	6.34	8.92	0.05
MPI 3 snow 01 126	13.03	5.05	12.76	3.50	1.28	5.01	33.85	23.56	12.91	7.33	9.42	-1.96
MPI 4 distributed 86 126	13.09	4.88	10.05	-7.56	-2.54	1.68	28.28	20.94	11.91	5.78	8.45	-4.06
MPI 4 distributed 91 126	14.39	6.69	14.95	-5.93	-3.32	2.84	33.46	19.47	13.07	7.31	7.51	-5.15
MPI 4 distributed 96 126	11.32	5.52	16.10	3.54	0.42	2.21	34.50	29.45	17.53	10.28	8.43	-4.14
MRI 1 lumped 86 126	25.05	17.11	13.97	-8.07	-5.85	-1.97	35.53	32.12	29.20	15.55	18.58	5.80
MRI 1 lumped 91 126	24.48	13.03	16.47	-4.37	-5.59	-2.63	38.50	34.04	29.58	16.08	18.61	6.68
MRI 1 lumped 96 126	26.63	15.30	16.09	-5.67	-5.60	-3.07	37.75	36.79	31.68	15.83	18.88	8.09
MRI 2 semi 86 126	27.58	12.83	9.34	-4.64	-3.75	-1.89	37.70	36.55	31.20	17.87	21.80	10.06
MRI 2 semi 91 126	29.12	13.99	13.81	-3.74	-3.81	-2.52	41.04	38.81	32.21	18.78	22.61	10.73
MRI 2 semi 96 126	29.72	12.96	12.22	-4.41	-4.39	-3.85	42.00	42.91	35.68	19.43	22.36	11.26
MRI 3 snow 96 126	30.06	16.66	11.23	-1.84	-2.78	-2.40	37.42	40.00	34.54	19.37	21.58	12.97
MRI 3 snow 01 126	27.82	13.76	8.83	-2.39	-3.66	-2.67	37.37	42.02	34.58	21.64	23.00	12.47
MRI 4 distributed 86 126	28.58	16.44	9.63	-9.76	-4.84	-2.98	32.32	37.68	30.51	17.30	19.66	10.10
MRI 4 distributed 91 126	28.07	16.01	13.97	-8.25	-5.94	-1.93	38.72	37.33	33.44	19.86	19.91	8.10
MRI 4 distributed 96 126	22.40	12.29	12.42	-1.46	-3.58	-4.28	38.62	48.31	41.28	26.32	21.71	9.50
TAI 1 lumped 86 126	12.21	13.94	22.84	0.19	-6.73	-18.71	-1.58	-11.54	-10.27	-7.45	0.86	-7.44
TAI 1 lumped 91 126	12.87	12.68	28.75	6.45	-5.44	-18.65	1.73	-9.14	-8.24	-5.14	3.53	-4.34
TAI 1 lumped 96 126	21.12	18.53	30.54	6.28	-4.32	-17.42	4.18	-5.11	-6.15	-5.04	7.60	3.29
TAI 2 semi 86 126	11.50	8.80	18.79	5.43	-4.43	-19.51	-2.08	-11.25	-11.11	-7.31	1.94	-5.45
TAI 2 semi 91 126	15.81	12.43	25.25	7.37	-4.17	-20.12	0.87	-9.07	-9.26	-5.15	4.79	-2.12
TAI 2 semi 96 126	23.59	16.74	27.64	8.65	-3.47	-19.90	4.23	-4.24	-6.43	-3.64	10.32	5.69
TAI 3 snow 96 126	25.56	21.48	25.27	10.87	-1.34	-17.15	3.19	-3.77	-5.17	-2.29	10.96	9.09
TAI 3 snow 01 126	19.38	15.95	21.91	10.02	-2.66	-18.46	0.49	-4.04	-7.49	-2.99	9.24	4.88
TAI 4 distributed 86 126	16.79	12.37	17.48	-1.83	-2.90	-15.50	-0.33	-6.30	-10.34	-6.83	3.90	-2.76
TAI 4 distributed 91 126	16.86	13.56	23.12	-0.19	-5.27	-17.05	2.40	-6.87	-8.97	-5.66	2.76	-3.68
TAI 4 distributed 96 126	17.92	14.04	25.89	11.02	-1.35	-18.12	2.67	-0.86	-8.09	-2.94	10.02	3.20
CMCC 1 lumped 86 245	20.57	20.92	16.81	-11.36	-20.83	-28.21	-7.00	-11.11	-6.09	-5.67	2.64	-5.73
CMCC 1 lumped 91 245	21.91	18.50	20.24	-7.19	-20.25	-28.32	-3.84	-8.82	-4.22	-3.79	4.53	-3.11
CMCC 1 lumped 96 245	26.55	22.65	21.96	-6.73	-19.05	-26.92	-1.78	-5.15	-2.09	-4.07	6.60	0.44
CMCC 2 semi 86 245	22.16	15.92	11.98	-8.05	-19.94	-30.13	-8.15	-10.42	-6.26	-4.89	4.36	-2.89
CMCC 2 semi 91 245	24.62	18.44	17.04	-6.89	-20.11	-30.69	-5.49	-8.49	-4.79	-3.34	6.15	-1.44

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Tab. 6.50: Changes in discharge for seasonal runoff compared to 30 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
CMCC 2 semi 96 245	29.65	20.55	18.19	-5.01	-19.19	-29.95	-2.28	-3.65	-1.45	-1.97	9.44	2.88
CMCC 3 snow 96 245	30.39	24.84	17.29	-2.62	-16.58	-26.92	-2.61	-3.51	-0.59	-1.14	9.60	5.31
CMCC 3 snow 01 245	26.12	20.40	14.56	-2.89	-17.70	-28.35	-5.47	-3.85	-3.00	-1.24	8.84	2.86
CMCC 4 distributed 86 245	24.28	19.47	12.49	-11.81	-18.19	-27.40	-7.83	-6.05	-4.58	-3.59	5.80	-0.02
CMCC 4 distributed 91 245	24.51	19.39	16.14	-11.52	-20.84	-29.11	-5.83	-7.40	-4.28	-2.88	5.20	-1.49
CMCC 4 distributed 96 245	22.35	17.38	17.03	-2.54	-17.85	-30.66	-6.12	-1.26	-1.33	1.42	10.84	3.78
EC 1 lumped 86 245	-55.72	-56.30	-60.72	-65.88	-63.64	-65.48	-57.91	-61.99	-61.24	-61.39	-60.59	-63.27
EC 1 lumped 91 245	-55.45	-57.13	-58.74	-63.45	-63.32	-65.48	-56.45	-60.92	-60.35	-60.44	-59.67	-62.03
EC 1 lumped 96 245	-50.82	-52.82	-56.76	-62.06	-61.82	-64.14	-54.84	-58.73	-59.11	-60.77	-58.80	-58.85
EC 2 semi 86 245	-57.40	-59.92	-62.92	-64.66	-63.42	-66.36	-58.65	-62.16	-61.78	-61.61	-60.87	-63.46
EC 2 semi 91 245	-55.46	-57.83	-60.49	-64.00	-63.12	-66.28	-57.08	-60.98	-60.80	-60.59	-59.80	-61.92
EC 2 semi 96 245	-51.03	-54.55	-58.24	-61.46	-61.81	-65.43	-55.03	-58.48	-59.39	-60.66	-58.86	-59.12
EC 3 snow 96 245	-48.85	-51.83	-57.80	-60.14	-60.44	-63.92	-55.03	-57.97	-58.44	-59.56	-57.38	-56.69
EC 3 snow 01 245	-52.35	-54.79	-59.28	-60.40	-61.08	-64.69	-56.41	-58.45	-59.78	-60.09	-58.46	-59.67
EC 4 distributed 86 245	-53.92	-57.99	-62.74	-68.40	-64.72	-66.66	-59.60	-61.25	-62.46	-62.37	-60.31	-61.96
EC 4 distributed 91 245	-52.98	-55.78	-60.28	-67.62	-65.51	-67.12	-58.54	-61.58	-62.14	-62.17	-61.35	-62.32
EC 4 distributed 96 245	-51.14	-55.31	-57.23	-61.26	-62.88	-66.68	-57.28	-58.07	-60.67	-61.08	-59.03	-59.67
GFDL 1 lumped 86 245	-59.70	-64.42	-72.27	-78.13	-77.16	-74.70	-61.70	-57.99	-56.02	-58.41	-55.81	-63.39
GFDL 1 lumped 91 245	-60.71	-65.74	-71.32	-76.82	-77.18	-74.90	-60.69	-57.31	-55.98	-58.31	-55.82	-63.15
GFDL 1 lumped 96 245	-59.39	-64.59	-71.27	-76.65	-76.56	-74.36	-60.31	-55.88	-55.15	-57.74	-54.89	-62.42
GFDL 2 semi 86 245	-59.33	-66.28	-73.32	-77.11	-76.87	-75.01	-61.26	-56.26	-54.90	-56.93	-53.86	-61.51
GFDL 2 semi 91 245	-58.79	-65.13	-71.85	-76.84	-76.81	-74.95	-60.03	-55.25	-54.42	-56.51	-53.42	-61.27
GFDL 2 semi 96 245	-58.64	-65.45	-72.03	-76.22	-76.53	-74.82	-59.23	-53.26	-53.00	-55.25	-52.39	-60.94
GFDL 3 snow 96 245	-58.33	-64.14	-72.10	-75.64	-75.93	-74.24	-60.29	-54.61	-53.91	-56.09	-53.68	-60.67
GFDL 3 snow 01 245	-59.33	-65.21	-72.44	-75.46	-76.16	-74.52	-60.71	-53.82	-53.62	-54.83	-52.71	-60.42
GFDL 4 distributed 86 245	-57.70	-64.84	-73.09	-78.94	-77.38	-75.49	-63.19	-56.29	-55.53	-56.94	-54.65	-61.34
GFDL 4 distributed 91 245	-58.51	-64.59	-71.84	-78.57	-77.55	-75.11	-61.26	-56.43	-54.69	-56.30	-54.26	-62.17
GFDL 4 distributed 96 245	-60.94	-66.69	-71.09	-75.70	-76.75	-75.77	-61.13	-52.20	-51.24	-51.98	-52.06	-61.92
MPI 1 lumped 86 245	-64.96	-68.22	-70.13	-77.06	-78.41	-78.50	-71.53	-70.30	-65.69	-65.57	-61.85	-67.59
MPI 1 lumped 91 245	-65.35	-69.03	-69.10	-75.75	-78.22	-78.57	-70.71	-69.64	-65.32	-65.14	-61.58	-67.30
MPI 1 lumped 96 245	-64.79	-68.69	-69.36	-76.00	-78.11	-78.46	-70.64	-68.56	-64.07	-64.38	-60.69	-66.52
MPI 2 semi 86 245	-64.17	-69.02	-70.94	-75.92	-77.96	-78.69	-71.37	-69.39	-64.91	-64.12	-59.82	-65.78
MPI 2 semi 91 245	-63.46	-68.43	-69.57	-75.54	-77.98	-78.82	-70.60	-68.70	-64.33	-63.68	-59.43	-65.37
MPI 2 semi 96 245	-63.65	-69.05	-70.11	-75.53	-78.03	-78.96	-70.21	-67.20	-62.30	-61.89	-58.15	-64.86
MPI 3 snow 96 245	-63.88	-68.32	-70.64	-75.03	-77.47	-78.38	-70.71	-67.83	-63.06	-62.88	-59.65	-64.95
MPI 3 snow 01 245	-64.60	-69.23	-71.18	-75.05	-77.73	-78.61	-71.09	-67.55	-63.22	-61.71	-58.88	-64.75

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Tab. 6.50: Changes in discharge for seasonal runoff compared to 30 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
MPI 4 distributed 86 245	-63.08	-68.26	-71.22	-77.28	-77.71	-78.38	-71.79	-68.47	-64.44	-63.19	-59.67	-65.32
MPI 4 distributed 91 245	-63.76	-68.35	-69.99	-76.83	-78.05	-78.27	-70.56	-68.64	-63.86	-62.71	-59.50	-66.15
MPI 4 distributed 96 245	-65.81	-69.74	-70.16	-74.76	-77.48	-78.92	-70.84	-66.07	-60.75	-58.57	-57.38	-66.22
MRI 1 lumped 86 245	-82.68	-82.68	-82.00	-85.84	-85.21	-84.73	-79.72	-81.06	-80.76	-81.77	-82.42	-85.28
MRI 1 lumped 91 245	-82.63	-83.00	-81.61	-85.30	-85.23	-84.88	-79.24	-80.77	-80.61	-81.62	-82.27	-85.06
MRI 1 lumped 96 245	-81.73	-82.13	-80.98	-85.02	-84.93	-84.67	-78.98	-80.08	-80.11	-81.68	-82.30	-84.56
MRI 2 semi 86 245	-82.85	-83.60	-82.97	-85.50	-85.11	-85.02	-79.81	-80.89	-80.87	-81.76	-82.38	-85.14
MRI 2 semi 91 245	-82.33	-83.23	-82.27	-85.43	-85.12	-85.11	-79.27	-80.54	-80.63	-81.49	-82.13	-84.86
MRI 2 semi 96 245	-81.61	-82.59	-81.68	-84.90	-84.91	-85.08	-78.82	-79.74	-80.02	-81.46	-82.21	-84.56
MRI 3 snow 96 245	-81.12	-81.79	-81.63	-84.30	-84.46	-84.57	-79.03	-79.70	-79.78	-81.12	-81.80	-83.81
MRI 3 snow 01 245	-81.94	-82.46	-82.01	-84.24	-84.67	-84.78	-79.41	-79.72	-80.21	-81.14	-81.87	-84.36
MRI 4 distributed 86 245	-82.62	-83.03	-82.63	-86.12	-85.45	-85.43	-80.82	-80.93	-81.35	-82.39	-82.86	-85.22
MRI 4 distributed 91 245	-82.08	-82.50	-81.93	-86.09	-85.77	-85.47	-80.16	-81.05	-81.09	-82.02	-82.98	-85.22
MRI 4 distributed 96 245	-81.95	-82.28	-81.49	-84.43	-85.22	-85.74	-80.03	-79.58	-80.20	-81.35	-82.69	-84.71
TAI 1 lumped 86 245	-84.32	-84.55	-83.15	-85.79	-85.22	-86.32	-83.29	-84.95	-84.71	-84.38	-83.85	-86.64
TAI 1 lumped 91 245	-84.35	-84.85	-82.45	-85.06	-85.13	-86.37	-82.77	-84.58	-84.42	-84.06	-83.52	-86.31
TAI 1 lumped 96 245	-83.29	-83.97	-82.07	-84.95	-84.87	-86.14	-82.37	-83.74	-83.81	-83.82	-83.05	-85.52
TAI 2 semi 86 245	-84.51	-85.38	-83.87	-85.25	-84.98	-86.49	-83.30	-84.76	-84.75	-84.22	-83.61	-86.42
TAI 2 semi 91 245	-84.04	-85.02	-83.10	-85.10	-84.95	-86.58	-82.81	-84.37	-84.45	-83.90	-83.26	-86.08
TAI 2 semi 96 245	-83.19	-84.39	-82.59	-84.72	-84.76	-86.50	-82.23	-83.36	-83.67	-83.41	-82.66	-85.40
TAI 3 snow 96 245	-82.66	-83.58	-82.77	-84.26	-84.39	-86.04	-82.46	-83.43	-83.56	-83.29	-82.51	-84.75
TAI 3 snow 01 245	-83.56	-84.28	-83.17	-84.25	-84.55	-86.12	-82.76	-83.36	-83.94	-83.33	-82.64	-85.29
TAI 4 distributed 86 245	-83.98	-84.77	-83.87	-86.19	-85.27	-86.45	-83.63	-84.24	-84.61	-84.15	-83.50	-86.22
TAI 4 distributed 91 245	-83.86	-84.55	-83.08	-86.00	-85.48	-86.54	-83.11	-84.32	-84.40	-83.91	-83.67	-86.38
TAI 4 distributed 96 245	-83.76	-84.39	-82.61	-84.45	-84.91	-86.62	-82.84	-82.86	-83.66	-82.90	-82.67	-85.61
CMCC 1 lumped 86 370	-14.80	-13.98	-15.24	-26.40	-30.55	-40.81	-30.04	-36.42	-29.59	-28.25	-25.19	-35.64
CMCC 1 lumped 91 370	-12.62	-14.76	-12.07	-22.18	-30.05	-40.62	-27.32	-34.09	-27.09	-25.57	-22.01	-32.38
CMCC 1 lumped 96 370	-4.39	-7.07	-7.54	-19.28	-27.21	-37.35	-23.59	-30.39	-24.48	-25.63	-18.51	-27.04
CMCC 2 semi 86 370	-15.50	-20.15	-20.06	-23.75	-29.96	-43.03	-32.15	-37.54	-30.53	-28.46	-25.13	-34.99
CMCC 2 semi 91 370	-12.55	-16.54	-15.59	-22.72	-29.88	-43.08	-29.69	-35.60	-28.53	-26.17	-22.03	-32.64
CMCC 2 semi 96 370	-3.65	-10.07	-10.25	-17.15	-26.97	-40.31	-25.06	-30.87	-24.77	-24.59	-16.59	-26.23
CMCC 3 snow 96 370	-1.16	-5.24	-10.26	-15.08	-24.54	-37.26	-24.35	-29.58	-23.36	-23.34	-15.90	-23.29
CMCC 3 snow 01 370	-7.82	-10.86	-13.36	-15.18	-25.06	-38.88	-27.48	-31.19	-26.43	-24.58	-18.22	-27.36
CMCC 4 distributed 86 370	-10.32	-14.06	-17.73	-28.81	-30.81	-41.49	-31.54	-33.19	-28.44	-26.44	-20.36	-29.71
CMCC 4 distributed 91 370	-8.62	-12.00	-14.13	-29.04	-33.83	-44.02	-32.20	-35.41	-29.80	-27.16	-21.91	-29.96
CMCC 4 distributed 96 370	-4.62	-10.98	-9.85	-17.03	-28.41	-42.83	-30.89	-31.39	-27.35	-23.48	-13.44	-20.86

Continued on next page

Tab. 6.50: Changes in discharge for seasonal runoff compared to 30 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
EC 1 lumped 86 370	-43.63	-46.79	-59.45	-66.53	-62.90	-62.74	-55.77	-59.64	-56.03	-53.37	-47.41	-51.96
EC 1 lumped 91 370	-43.51	-48.14	-57.22	-63.89	-62.57	-62.71	-54.30	-58.49	-55.04	-52.34	-46.49	-50.72
EC 1 lumped 96 370	-38.57	-44.08	-56.06	-63.09	-61.14	-61.44	-53.04	-56.43	-53.43	-51.51	-43.57	-46.41
EC 2 semi 86 370	-44.47	-50.45	-61.42	-65.03	-62.34	-63.11	-55.93	-59.47	-56.24	-52.96	-46.51	-50.97
EC 2 semi 91 370	-41.77	-47.68	-58.61	-64.28	-61.93	-62.86	-54.15	-58.08	-54.94	-51.56	-44.99	-48.96
EC 2 semi 96 370	-37.34	-45.46	-57.54	-62.63	-60.93	-62.24	-52.65	-55.89	-53.10	-49.98	-41.58	-44.97
EC 3 snow 96 370	-35.91	-43.43	-56.96	-61.38	-59.88	-61.14	-53.13	-55.59	-52.56	-49.74	-41.57	-43.45
EC 3 snow 01 370	-39.09	-46.56	-58.35	-61.81	-60.64	-61.87	-54.30	-56.11	-54.15	-50.21	-42.21	-45.74
EC 4 distributed 86 370	-41.07	-48.50	-61.99	-68.90	-63.77	-63.65	-56.96	-58.07	-56.13	-52.69	-45.68	-49.55
EC 4 distributed 91 370	-40.39	-46.56	-59.44	-68.42	-64.37	-63.45	-55.39	-58.08	-55.39	-51.88	-45.78	-49.97
EC 4 distributed 96 370	-40.53	-48.25	-56.06	-62.17	-62.04	-63.36	-54.51	-54.78	-53.23	-47.89	-40.99	-47.64
GFDL 1 lumped 86 370	-60.88	-62.89	-68.37	-74.42	-74.72	-73.97	-64.14	-64.40	-64.98	-66.02	-64.30	-68.69
GFDL 1 lumped 91 370	-61.47	-63.86	-67.03	-72.73	-74.55	-74.09	-63.22	-63.74	-64.67	-65.60	-63.84	-68.07
GFDL 1 lumped 96 370	-59.40	-62.27	-66.68	-72.39	-73.85	-73.61	-62.97	-62.71	-64.27	-65.64	-63.11	-66.79
GFDL 2 semi 86 370	-60.94	-65.06	-69.59	-73.20	-74.42	-74.39	-64.20	-63.63	-64.88	-65.63	-63.50	-67.57
GFDL 2 semi 91 370	-60.09	-63.60	-67.83	-72.82	-74.34	-74.49	-63.29	-62.93	-64.42	-65.04	-62.75	-67.03
GFDL 2 semi 96 370	-58.77	-63.13	-67.59	-71.84	-73.90	-74.44	-62.80	-61.65	-63.81	-64.76	-61.77	-65.87
GFDL 3 snow 96 370	-58.25	-61.67	-67.62	-71.12	-73.06	-73.57	-63.17	-61.96	-63.60	-64.57	-62.05	-65.14
GFDL 3 snow 01 370	-59.88	-63.28	-68.26	-71.01	-73.34	-74.04	-63.85	-61.81	-64.08	-64.45	-61.92	-65.65
GFDL 4 distributed 86 370	-59.00	-63.68	-69.70	-75.59	-74.74	-74.48	-65.24	-62.88	-65.25	-66.21	-64.05	-67.20
GFDL 4 distributed 91 370	-59.59	-63.17	-68.27	-75.21	-75.27	-74.61	-64.12	-63.44	-64.92	-65.57	-63.82	-67.73
GFDL 4 distributed 96 370	-61.13	-64.72	-66.98	-71.36	-73.92	-75.13	-64.43	-60.75	-63.55	-63.84	-62.14	-66.68
MPI 1 lumped 86 370	-68.36	-69.00	-72.63	-79.37	-79.36	-78.92	-72.51	-74.33	-73.73	-74.09	-72.45	-75.76
MPI 1 lumped 91 370	-68.71	-69.83	-71.69	-78.15	-79.20	-78.99	-71.75	-73.78	-73.37	-73.72	-72.13	-75.26
MPI 1 lumped 96 370	-67.38	-68.78	-71.63	-78.14	-78.91	-78.79	-71.56	-72.87	-72.82	-73.76	-71.78	-74.54
MPI 2 semi 86 370	-68.27	-70.42	-73.68	-78.44	-79.03	-79.17	-72.49	-73.90	-73.67	-73.76	-71.86	-75.01
MPI 2 semi 91 370	-67.62	-69.63	-72.35	-78.17	-79.02	-79.30	-71.79	-73.37	-73.29	-73.36	-71.46	-74.64
MPI 2 semi 96 370	-66.80	-69.38	-72.47	-77.84	-78.86	-79.33	-71.32	-72.26	-72.47	-73.04	-70.96	-73.96
MPI 3 snow 96 370	-66.50	-68.25	-72.69	-77.15	-78.28	-78.69	-71.68	-72.39	-72.33	-72.93	-71.00	-73.36
MPI 3 snow 01 370	-67.84	-69.42	-73.36	-77.26	-78.63	-78.98	-72.13	-72.31	-72.84	-72.84	-71.00	-73.88
MPI 4 distributed 86 370	-67.26	-69.38	-73.60	-79.68	-79.09	-79.33	-73.29	-73.26	-73.64	-73.82	-71.82	-74.46
MPI 4 distributed 91 370	-67.43	-69.27	-72.44	-79.42	-79.61	-79.39	-72.38	-73.56	-73.33	-73.39	-71.82	-74.81
MPI 4 distributed 96 370	-68.59	-70.37	-72.16	-77.05	-78.75	-79.73	-72.36	-71.56	-72.21	-72.03	-70.75	-74.14
MRI 1 lumped 86 370	-76.70	-77.62	-78.79	-82.68	-81.42	-80.83	-74.19	-75.38	-77.14	-79.55	-79.58	-80.77
MRI 1 lumped 91 370	-76.87	-78.19	-78.17	-81.76	-81.35	-80.96	-73.59	-75.03	-77.01	-79.39	-79.46	-80.55
MRI 1 lumped 96 370	-75.90	-77.43	-78.00	-81.75	-81.18	-80.84	-73.55	-74.24	-76.57	-79.55	-79.57	-79.89

Continued on next page

Tab. 6.50: Changes in discharge for seasonal runoff compared to 30 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
MRI 2 semi 86 370	-76.54	-78.57	-79.72	-81.94	-81.07	-80.90	-73.80	-74.64	-76.99	-79.35	-79.25	-80.16
MRI 2 semi 91 370	-76.01	-78.07	-78.77	-81.77	-81.05	-81.00	-73.18	-74.24	-76.78	-79.10	-79.01	-79.88
MRI 2 semi 96 370	-75.33	-77.84	-78.71	-81.45	-81.01	-81.09	-72.87	-73.24	-76.22	-79.24	-79.23	-79.41
MRI 3 snow 96 370	-75.12	-76.97	-78.83	-80.95	-80.60	-80.70	-73.60	-73.68	-76.20	-79.04	-79.09	-78.93
MRI 3 snow 01 370	-75.83	-77.60	-79.21	-80.93	-80.69	-80.69	-73.67	-73.27	-76.35	-78.83	-79.01	-79.27
MRI 4 distributed 86 370	-76.05	-77.98	-79.69	-83.20	-81.56	-81.32	-75.05	-74.31	-76.83	-79.45	-79.50	-80.08
MRI 4 distributed 91 370	-76.01	-77.83	-78.87	-82.97	-81.84	-81.20	-74.04	-74.61	-76.55	-79.11	-79.65	-80.31
MRI 4 distributed 96 370	-76.51	-78.31	-78.64	-81.07	-81.13	-81.42	-73.93	-72.42	-75.55	-78.69	-79.62	-79.86
TAI 1 lumped 86 370	-79.28	-79.46	-79.00	-84.66	-87.48	-89.39	-86.39	-86.54	-85.09	-83.65	-81.06	-82.72
TAI 1 lumped 91 370	-78.99	-79.64	-78.10	-83.78	-87.39	-89.36	-85.81	-86.04	-84.65	-83.13	-80.32	-81.94
TAI 1 lumped 96 370	-77.79	-78.83	-78.01	-83.90	-87.12	-88.89	-85.30	-85.16	-83.98	-82.47	-78.89	-80.52
TAI 2 semi 86 370	-79.02	-80.17	-79.71	-84.00	-87.41	-89.79	-86.71	-86.57	-85.25	-83.50	-80.47	-81.92
TAI 2 semi 91 370	-78.34	-79.66	-78.74	-83.79	-87.47	-89.80	-86.22	-86.09	-84.83	-83.00	-79.67	-81.29
TAI 2 semi 96 370	-77.16	-79.10	-78.61	-83.71	-87.29	-89.49	-85.53	-84.91	-83.75	-81.76	-77.62	-79.62
TAI 3 snow 96 370	-76.97	-78.32	-78.92	-83.22	-86.78	-88.96	-85.47	-84.91	-83.73	-81.82	-78.11	-79.28
TAI 3 snow 01 370	-78.02	-79.22	-79.55	-83.35	-87.05	-89.33	-86.04	-84.97	-84.04	-81.80	-78.30	-79.81
TAI 4 distributed 86 370	-78.52	-79.58	-79.86	-84.60	-86.58	-88.75	-86.20	-85.58	-84.94	-83.34	-80.39	-81.74
TAI 4 distributed 91 370	-78.91	-79.87	-79.13	-84.54	-87.14	-89.08	-85.91	-85.66	-84.72	-83.13	-80.55	-82.28
TAI 4 distributed 96 370	-78.92	-79.93	-79.05	-83.22	-86.82	-89.46	-86.14	-84.61	-84.00	-81.43	-78.07	-80.56
CMCC 1 lumped 86 585	7.24	-4.43	-10.00	-24.27	-27.61	-33.73	-20.93	-29.59	-21.55	-17.95	-3.45	-11.92
CMCC 1 lumped 91 585	8.66	-5.98	-6.86	-20.47	-27.16	-33.82	-18.39	-27.54	-19.28	-15.23	-0.37	-8.22
CMCC 1 lumped 96 585	16.02	-0.32	-4.39	-19.03	-25.49	-32.10	-16.20	-24.87	-16.98	-15.22	4.57	-1.84
CMCC 2 semi 86 585	7.67	-9.79	-14.73	-21.94	-27.09	-35.73	-22.92	-30.76	-22.52	-17.90	-2.51	-9.74
CMCC 2 semi 91 585	10.35	-7.10	-10.51	-21.29	-27.22	-36.13	-20.62	-29.00	-20.58	-15.59	0.50	-7.38
CMCC 2 semi 96 585	18.09	-3.05	-7.81	-17.77	-25.61	-34.97	-17.60	-25.57	-17.28	-13.70	7.83	0.70
CMCC 3 snow 96 585	19.77	1.74	-7.92	-15.22	-23.07	-32.08	-16.96	-24.00	-15.80	-12.46	8.03	3.57
CMCC 3 snow 01 585	14.00	-3.06	-10.92	-15.73	-24.28	-33.64	-19.77	-25.19	-18.98	-13.84	5.47	-0.30
CMCC 4 distributed 86 585	11.73	-4.15	-12.80	-25.61	-26.57	-34.04	-23.33	-28.01	-22.42	-16.88	1.50	-4.33
CMCC 4 distributed 91 585	12.18	-3.89	-9.67	-26.13	-29.79	-36.32	-23.08	-29.44	-22.67	-16.82	0.34	-6.06
CMCC 4 distributed 96 585	13.21	-4.15	-7.79	-17.21	-26.67	-37.43	-23.50	-26.48	-21.04	-12.30	11.34	3.68
EC 1 lumped 86 585	-55.00	-53.88	-62.72	-69.27	-68.40	-67.48	-56.41	-58.11	-58.51	-60.06	-60.79	-64.97
EC 1 lumped 91 585	-54.65	-55.02	-60.77	-66.96	-68.23	-67.49	-54.83	-56.88	-57.67	-59.18	-59.89	-63.91
EC 1 lumped 96 585	-49.80	-50.41	-58.85	-65.69	-66.50	-65.79	-52.97	-53.95	-55.69	-58.68	-58.86	-60.98
EC 2 semi 86 585	-56.25	-57.67	-64.89	-68.15	-68.35	-68.39	-56.86	-57.70	-58.78	-59.88	-60.64	-64.82
EC 2 semi 91 585	-54.07	-55.32	-62.35	-67.51	-68.07	-68.07	-55.05	-56.23	-57.75	-58.82	-59.48	-63.34
EC 2 semi 96 585	-49.50	-52.06	-60.34	-65.30	-66.74	-66.92	-52.61	-52.71	-55.34	-58.02	-58.43	-60.96

Continued on next page

Tab. 6.50: Changes in discharge for seasonal runoff compared to 30 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
EC 3 snow 96 585	-47.48	-49.59	-59.54	-63.93	-65.34	-65.55	-52.86	-52.74	-54.71	-57.28	-57.43	-58.85
EC 3 snow 01 585	-50.82	-52.66	-60.74	-63.99	-65.89	-66.34	-54.22	-52.98	-55.90	-57.53	-58.06	-61.32
EC 4 distributed 86 585	-52.84	-55.64	-65.24	-71.68	-69.71	-69.33	-59.09	-56.98	-58.94	-60.29	-60.02	-63.38
EC 4 distributed 91 585	-52.00	-53.25	-62.52	-71.05	-70.16	-69.22	-57.37	-56.90	-58.22	-59.57	-60.81	-63.89
EC 4 distributed 96 585	-50.28	-53.66	-58.64	-64.60	-67.58	-68.58	-55.38	-51.48	-54.87	-57.01	-58.43	-61.67
GFDL 1 lumped 86 585	-51.68	-54.93	-58.25	-68.84	-69.25	-66.62	-54.26	-54.29	-54.94	-57.06	-51.94	-57.26
GFDL 1 lumped 91 585	-51.61	-56.46	-57.07	-67.10	-69.13	-66.89	-53.11	-53.55	-54.77	-56.67	-51.67	-56.59
GFDL 1 lumped 96 585	-51.31	-55.97	-57.64	-67.67	-68.97	-66.71	-53.16	-52.30	-54.14	-56.30	-50.63	-56.12
GFDL 2 semi 86 585	-49.90	-56.12	-59.56	-67.49	-68.76	-66.84	-53.57	-52.61	-54.11	-55.78	-49.84	-54.87
GFDL 2 semi 91 585	-49.45	-55.71	-57.94	-66.96	-68.81	-67.07	-52.52	-51.87	-53.85	-55.47	-49.35	-54.57
GFDL 2 semi 96 585	-49.64	-56.59	-58.79	-67.14	-68.92	-67.29	-52.06	-50.12	-52.74	-54.47	-48.06	-54.04
GFDL 3 snow 96 585	-49.78	-55.24	-59.45	-66.53	-68.16	-66.59	-53.27	-51.25	-53.20	-54.96	-49.39	-53.83
GFDL 3 snow 01 585	-50.16	-56.33	-60.11	-66.43	-68.33	-66.63	-53.26	-50.09	-52.91	-53.81	-48.40	-53.41
GFDL 4 distributed 86 585	-49.52	-54.74	-59.70	-68.98	-68.69	-67.06	-55.15	-51.74	-53.85	-54.96	-50.55	-54.77
GFDL 4 distributed 91 585	-50.96	-55.87	-58.23	-68.25	-68.79	-66.37	-52.88	-52.03	-53.12	-54.54	-50.36	-56.36
GFDL 4 distributed 96 585	-53.52	-57.87	-59.02	-66.02	-68.12	-67.18	-52.99	-48.16	-50.90	-51.56	-48.26	-55.63
MPI 1 lumped 86 585	-71.05	-72.24	-73.53	-77.63	-75.30	-73.85	-69.76	-75.44	-76.02	-76.02	-74.81	-77.37
MPI 1 lumped 91 585	-71.23	-72.75	-72.51	-76.34	-75.01	-73.86	-69.02	-74.98	-75.66	-75.61	-74.42	-76.89
MPI 1 lumped 96 585	-69.70	-71.61	-72.01	-76.12	-74.70	-73.84	-69.02	-74.09	-75.03	-75.65	-74.03	-75.87
MPI 2 semi 86 585	-71.13	-73.52	-74.56	-76.58	-74.62	-73.65	-69.37	-75.15	-76.06	-75.80	-74.41	-76.81
MPI 2 semi 91 585	-70.36	-72.71	-73.20	-76.18	-74.47	-73.77	-68.74	-74.76	-75.67	-75.36	-73.94	-76.38
MPI 2 semi 96 585	-69.14	-72.10	-72.76	-75.57	-74.26	-73.94	-68.43	-73.79	-74.97	-75.20	-73.44	-75.45
MPI 3 snow 96 585	-68.78	-71.07	-73.07	-75.06	-73.92	-73.56	-69.08	-73.73	-74.75	-75.03	-73.31	-74.71
MPI 3 snow 01 585	-70.07	-72.14	-73.62	-75.17	-74.13	-73.48	-69.06	-73.60	-75.29	-75.02	-73.45	-75.38
MPI 4 distributed 86 585	-69.92	-72.48	-74.34	-78.14	-75.27	-74.33	-70.15	-73.95	-75.35	-75.26	-73.74	-76.02
MPI 4 distributed 91 585	-69.81	-72.02	-73.17	-77.78	-75.49	-74.19	-69.28	-74.35	-75.23	-75.04	-73.97	-76.33
MPI 4 distributed 96 585	-70.28	-72.47	-72.55	-75.06	-74.42	-74.26	-68.95	-72.54	-74.72	-74.44	-73.06	-75.41
MRI 1 lumped 86 585	-80.43	-81.48	-83.69	-86.84	-85.93	-86.10	-81.60	-81.49	-80.26	-81.28	-81.10	-83.05
MRI 1 lumped 91 585	-80.52	-81.95	-83.24	-86.15	-85.93	-86.19	-81.08	-81.11	-80.04	-81.03	-80.88	-82.79
MRI 1 lumped 96 585	-79.31	-80.92	-82.82	-85.90	-85.56	-85.80	-80.68	-80.33	-79.31	-80.79	-80.55	-81.80
MRI 2 semi 86 585	-80.56	-82.53	-84.56	-86.41	-85.80	-86.38	-81.71	-81.27	-80.28	-81.07	-80.78	-82.63
MRI 2 semi 91 585	-79.98	-82.01	-83.79	-86.28	-85.76	-86.37	-81.08	-80.79	-79.89	-80.68	-80.41	-82.23
MRI 2 semi 96 585	-79.01	-81.47	-83.45	-85.76	-85.50	-86.17	-80.49	-79.82	-78.86	-80.19	-80.00	-81.38
MRI 3 snow 96 585	-78.61	-80.53	-83.41	-85.26	-85.10	-85.72	-80.72	-79.90	-78.83	-80.08	-79.91	-80.86
MRI 3 snow 01 585	-79.45	-81.25	-83.81	-85.27	-85.29	-85.91	-81.12	-79.99	-79.22	-79.98	-79.92	-81.40
MRI 4 distributed 86 585	-79.88	-81.79	-84.17	-87.30	-86.15	-86.51	-82.49	-81.15	-80.53	-81.49	-81.13	-82.53

Continued on next page

Tab. 6.50: Changes in discharge for seasonal runoff compared to 30 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
MRI 4 distributed 91 585	-79.62	-81.41	-83.47	-87.18	-86.44	-86.55	-81.82	-81.21	-80.21	-81.03	-81.24	-82.65
MRI 4 distributed 96 585	-79.55	-81.54	-82.99	-85.43	-85.81	-86.70	-81.64	-79.60	-78.67	-79.49	-80.25	-81.78
TAI 1 lumped 86 585	-78.86	-77.15	-76.72	-82.57	-83.97	-85.40	-82.09	-84.11	-83.48	-83.07	-82.39	-83.42
TAI 1 lumped 91 585	-78.48	-77.25	-75.59	-81.39	-83.84	-85.51	-81.58	-83.70	-83.13	-82.61	-81.75	-82.75
TAI 1 lumped 96 585	-76.97	-76.31	-75.55	-81.69	-83.76	-85.33	-81.19	-82.81	-82.50	-82.26	-80.68	-81.18
TAI 2 semi 86 585	-78.15	-77.56	-77.28	-81.62	-83.70	-85.67	-82.22	-84.03	-83.58	-82.87	-81.75	-82.42
TAI 2 semi 91 585	-77.24	-76.90	-76.14	-81.28	-83.76	-85.85	-81.77	-83.64	-83.23	-82.41	-80.94	-81.65
TAI 2 semi 96 585	-75.71	-76.19	-76.01	-81.38	-83.82	-85.87	-81.23	-82.62	-82.39	-81.68	-79.42	-79.90
TAI 3 snow 96 585	-75.94	-75.56	-76.61	-81.03	-83.35	-85.36	-81.41	-82.61	-82.32	-81.71	-79.98	-79.80
TAI 3 snow 01 585	-76.89	-76.41	-77.10	-81.14	-83.54	-85.54	-81.79	-82.62	-82.70	-81.60	-79.98	-80.24
TAI 4 distributed 86 585	-77.70	-77.29	-77.71	-82.67	-83.17	-84.88	-81.75	-82.75	-82.96	-82.57	-81.80	-82.45
TAI 4 distributed 91 585	-78.35	-77.64	-76.74	-82.26	-83.50	-84.98	-81.17	-82.86	-82.76	-82.32	-81.90	-83.06
TAI 4 distributed 96 585	-77.95	-77.44	-76.60	-80.82	-83.25	-85.51	-81.43	-81.81	-82.35	-81.38	-80.30	-81.55

Tab. 6.51: Changes in discharge for seasonal runoff compared to 10 years historical period [%]

Variant	1	2	3	4	5	6	7	8	9	10	11	12
CMCC 1 lumped 86 126	82.56	33.08	3.17	-32.16	-32.98	-45.47	-21.14	-26.22	-22.15	-13.78	9.31	39.72
CMCC 1 lumped 91 126	81.89	30.87	1.73	-24.60	-33.13	-46.23	-18.40	-23.96	-19.34	-11.76	11.78	40.69
CMCC 1 lumped 96 126	90.68	33.75	2.34	-24.83	-32.72	-45.98	-15.91	-22.40	-19.88	-13.60	14.13	49.70
CMCC 2 semi 86 126	88.28	24.14	-8.44	-29.99	-33.48	-48.25	-22.77	-26.53	-23.29	-13.77	9.97	44.27
CMCC 2 semi 91 126	93.01	27.97	-2.84	-27.40	-34.27	-49.09	-20.14	-24.20	-19.99	-11.30	13.30	45.43
CMCC 2 semi 96 126	99.88	26.71	-6.31	-24.18	-34.16	-49.98	-16.79	-22.61	-20.89	-12.47	17.10	55.94
CMCC 3 snow 96 126	102.68	33.41	-7.06	-21.24	-30.97	-46.61	-16.18	-21.43	-19.32	-10.79	15.87	56.21
CMCC 3 snow 01 126	103.25	26.45	-8.11	-25.38	-30.84	-48.27	-19.18	-22.27	-22.90	-10.90	16.05	54.58
CMCC 4 distributed 86 126	100.10	25.91	-2.08	-34.95	-30.99	-45.60	-25.04	-25.97	-26.40	-17.21	7.76	56.32
CMCC 4 distributed 91 126	85.73	23.47	1.44	-32.45	-36.30	-47.95	-23.69	-26.57	-24.73	-15.94	8.62	44.16
CMCC 4 distributed 96 126	68.93	18.81	-7.43	-20.81	-33.16	-50.90	-23.41	-24.59	-27.78	-14.49	15.98	50.19
EC 1 lumped 86 126	67.05	33.71	-11.85	-39.01	-30.94	-38.15	-14.47	-24.37	-26.88	-24.27	-18.43	17.47
EC 1 lumped 91 126	66.29	31.29	-11.05	-30.53	-30.59	-38.69	-11.41	-21.89	-24.04	-22.23	-16.37	18.62
EC 1 lumped 96 126	83.14	39.90	-9.43	-29.62	-28.63	-37.75	-8.26	-19.07	-24.30	-25.32	-16.50	31.61
EC 2 semi 86 126	63.67	20.47	-22.23	-36.67	-31.28	-40.51	-15.59	-24.57	-28.26	-24.88	-19.72	17.33
EC 2 semi 91 126	73.67	27.03	-15.83	-33.71	-31.22	-40.89	-12.34	-21.69	-24.66	-22.26	-16.85	21.41

Continued on next page

Tab. 6.51: Changes in discharge for seasonal runoff compared to 10 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
EC 2 semi 96 126	87.98	30.54	-17.60	-29.32	-29.89	-41.53	-8.47	-19.29	-25.95	-25.95	-17.66	32.17
EC 3 snow 96 126	96.45	38.69	-16.51	-25.92	-26.43	-37.91	-8.03	-17.86	-23.73	-23.05	-14.89	37.40
EC 3 snow 01 126	89.61	28.41	-18.40	-30.38	-26.67	-39.76	-10.87	-18.99	-27.42	-23.45	-16.06	29.51
EC 4 distributed 86 126	81.23	22.20	-18.35	-45.47	-32.65	-41.46	-21.29	-25.85	-32.98	-30.75	-22.31	25.67
EC 4 distributed 91 126	73.58	25.47	-12.67	-41.89	-36.77	-42.41	-18.53	-25.67	-30.64	-28.88	-23.34	17.68
EC 4 distributed 96 126	62.62	21.72	-14.96	-26.11	-30.44	-42.99	-14.97	-20.72	-32.87	-30.59	-21.22	20.75
GFDL 1 lumped 86 126	50.02	21.35	7.73	-22.96	-18.10	-23.19	16.95	9.54	3.23	5.19	14.44	29.75
GFDL 1 lumped 91 126	46.71	18.82	6.69	-13.66	-18.16	-24.42	19.74	11.44	5.02	6.06	15.50	28.70
GFDL 1 lumped 96 126	53.07	20.91	7.06	-14.23	-17.67	-25.29	20.43	13.15	3.95	4.32	15.23	34.81
GFDL 2 semi 86 126	51.80	13.18	-3.49	-19.36	-17.74	-24.90	18.48	13.01	3.24	6.44	16.13	33.67
GFDL 2 semi 91 126	56.92	16.59	2.63	-15.98	-18.17	-25.92	21.48	15.62	6.71	8.72	18.91	34.71
GFDL 2 semi 96 126	58.03	14.67	-0.99	-12.66	-18.35	-28.64	23.08	16.64	4.33	6.43	17.72	38.18
GFDL 3 snow 96 126	62.70	20.83	-2.80	-10.18	-15.40	-25.68	20.69	15.18	4.89	7.57	16.75	40.41
GFDL 3 snow 01 126	62.67	15.64	-2.50	-13.62	-13.70	-26.44	19.93	16.95	2.45	9.80	19.63	41.08
GFDL 4 distributed 86 126	60.30	13.36	1.17	-28.97	-17.99	-25.19	10.48	11.23	-1.79	-0.49	8.44	37.91
GFDL 4 distributed 91 126	50.90	12.91	6.31	-24.20	-21.60	-25.40	15.41	11.00	1.43	2.52	9.68	28.06
GFDL 4 distributed 96 126	34.97	9.14	-1.16	-8.82	-16.65	-28.71	16.77	17.61	-0.81	4.25	11.12	26.91
MPI 1 lumped 86 126	59.48	23.69	12.99	-21.33	-15.37	-16.97	21.64	7.43	-2.57	-3.99	3.29	24.26
MPI 1 lumped 91 126	55.74	21.33	11.60	-13.02	-15.31	-18.15	24.55	9.53	-0.51	-3.14	3.82	22.77
MPI 1 lumped 96 126	62.59	23.30	12.22	-13.99	-15.39	-19.58	24.86	11.79	-0.92	-6.02	1.17	28.02
MPI 2 semi 86 126	60.43	15.70	1.47	-18.37	-14.88	-18.39	23.81	10.59	-2.53	-3.06	3.88	26.42
MPI 2 semi 91 126	65.76	18.25	7.30	-15.14	-15.37	-19.51	26.79	13.05	0.68	-1.32	5.42	27.11
MPI 2 semi 96 126	67.85	16.86	3.53	-12.92	-15.95	-22.44	28.59	15.05	-0.69	-5.03	1.40	29.60
MPI 3 snow 96 126	72.35	22.73	1.64	-10.07	-13.17	-19.62	25.74	13.87	-0.14	-3.57	2.20	32.51
MPI 3 snow 01 126	71.96	17.61	1.61	-14.10	-12.21	-20.19	25.82	15.83	-2.66	-1.86	3.93	31.29
MPI 4 distributed 86 126	70.49	16.60	7.37	-25.55	-14.94	-20.18	14.43	9.87	-5.01	-7.36	-0.11	33.17
MPI 4 distributed 91 126	62.36	17.18	12.77	-20.94	-18.67	-20.40	19.72	9.35	-2.18	-4.81	-0.31	24.44
MPI 4 distributed 96 126	45.93	15.37	3.63	-7.75	-14.16	-23.00	22.70	17.18	-4.10	-5.96	-2.07	21.68
MRI 1 lumped 86 126	80.60	36.69	12.67	-23.58	-18.00	-21.67	26.09	24.86	15.96	7.89	15.94	42.62
MRI 1 lumped 91 126	77.00	32.47	10.29	-16.16	-18.36	-23.02	29.03	27.17	17.79	8.28	15.90	40.48
MRI 1 lumped 96 126	81.23	33.20	9.09	-18.11	-19.01	-24.78	28.98	28.08	16.04	4.97	13.16	44.54
MRI 2 semi 86 126	85.60	28.76	0.78	-21.18	-17.73	-23.39	27.92	29.44	16.95	9.46	17.43	47.35
MRI 2 semi 91 126	89.64	30.37	6.22	-18.48	-18.49	-24.57	31.39	32.61	20.45	10.96	18.84	47.06
MRI 2 semi 96 126	88.86	26.28	0.04	-17.74	-19.71	-27.83	33.06	33.50	17.93	6.94	14.40	48.47
MRI 3 snow 96 126	91.59	32.13	-1.51	-14.54	-17.00	-25.03	29.53	30.99	17.84	8.26	14.08	49.62
MRI 3 snow 01 126	94.45	27.37	-1.93	-18.99	-16.48	-26.03	29.14	33.14	16.03	11.23	16.83	50.62

Continued on next page

Tab. 6.51: Changes in discharge for seasonal runoff compared to 10 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
MRI 4 distributed 86 126	93.83	29.46	6.96	-27.32	-16.95	-23.84	18.03	25.08	10.78	2.73	10.21	52.83
MRI 4 distributed 91 126	81.77	27.42	11.80	-22.89	-20.87	-24.09	24.43	25.70	15.44	6.32	11.18	41.82
MRI 4 distributed 96 126	60.45	22.77	0.34	-12.21	-17.58	-27.89	26.45	34.26	15.28	7.72	9.93	38.99
TAI 1 lumped 86 126	62.05	33.00	21.45	-16.71	-18.77	-35.04	-8.44	-16.41	-19.46	-13.58	-1.39	24.78
TAI 1 lumped 91 126	60.49	32.07	21.92	-6.68	-18.23	-35.69	-5.23	-13.80	-16.59	-11.52	1.16	25.97
TAI 1 lumped 96 126	73.35	36.93	22.67	-7.73	-17.91	-35.91	-2.44	-11.15	-17.29	-13.95	2.41	38.11
TAI 2 semi 86 126	62.20	24.16	9.49	-12.86	-18.31	-37.14	-9.03	-15.86	-20.77	-13.92	-1.72	26.59
TAI 2 semi 91 126	70.09	28.58	16.90	-9.08	-18.80	-38.19	-6.03	-13.14	-17.34	-11.39	1.57	30.00
TAI 2 semi 96 126	79.95	30.51	13.79	-6.50	-18.94	-39.88	-2.34	-10.54	-18.67	-13.72	3.14	41.05
TAI 3 snow 96 126	84.97	37.60	10.92	-3.47	-15.77	-36.36	-2.73	-9.97	-16.94	-11.39	4.12	44.48
TAI 3 snow 01 126	81.61	29.82	9.85	-8.69	-15.62	-38.03	-5.54	-10.05	-20.24	-11.30	3.76	40.46
TAI 4 distributed 86 126	76.06	24.94	14.62	-20.93	-15.25	-33.67	-11.09	-14.87	-23.89	-18.40	-4.31	34.98
TAI 4 distributed 91 126	65.86	24.74	20.78	-16.11	-20.31	-35.80	-8.14	-14.76	-21.25	-16.32	-4.72	26.37
TAI 4 distributed 96 126	54.57	24.68	12.37	-1.08	-15.67	-38.32	-6.34	-10.26	-25.00	-17.23	-0.63	30.99
CMCC 1 lumped 86 245	74.13	41.15	15.49	-26.31	-31.04	-42.63	-13.48	-15.99	-15.71	-11.91	0.36	27.08
CMCC 1 lumped 91 245	73.35	38.89	13.87	-18.64	-31.03	-43.33	-10.41	-13.50	-12.93	-10.26	2.14	27.59
CMCC 1 lumped 96 245	81.11	41.69	14.60	-19.03	-30.55	-43.29	-8.03	-11.19	-13.72	-13.06	1.47	34.31
CMCC 2 semi 86 245	77.71	32.29	3.21	-24.00	-31.57	-45.44	-14.67	-15.09	-16.44	-11.67	0.62	30.02
CMCC 2 semi 91 245	83.03	35.46	9.23	-21.16	-32.31	-46.37	-11.95	-12.58	-13.27	-9.70	2.89	30.91
CMCC 2 semi 96 245	88.76	34.77	5.37	-18.26	-32.14	-47.42	-8.43	-9.99	-14.34	-12.22	2.32	37.29
CMCC 3 snow 96 245	92.08	41.40	3.85	-15.23	-28.79	-43.86	-8.21	-9.73	-12.93	-10.35	2.84	39.48
CMCC 3 snow 01 245	91.88	34.80	3.23	-19.40	-28.65	-45.55	-11.13	-9.87	-16.37	-9.70	3.38	37.75
CMCC 4 distributed 86 245	87.35	32.83	9.75	-28.97	-28.60	-43.01	-17.78	-14.65	-19.00	-15.56	-2.56	38.77
CMCC 4 distributed 91 245	76.71	31.14	13.93	-25.64	-33.41	-45.13	-15.53	-15.25	-17.19	-13.85	-2.45	29.25
CMCC 4 distributed 96 245	60.37	28.33	4.45	-13.17	-29.77	-47.76	-14.35	-10.62	-19.49	-13.51	0.11	31.72
EC 1 lumped 86 245	-36.06	-48.99	-61.17	-71.64	-68.33	-72.41	-60.84	-64.08	-65.21	-63.95	-61.46	-50.48
EC 1 lumped 91 245	-36.66	-49.76	-60.93	-67.95	-68.28	-72.71	-59.42	-62.93	-63.96	-63.10	-60.59	-50.00
EC 1 lumped 96 245	-29.62	-45.49	-59.37	-67.07	-67.24	-72.17	-57.72	-61.36	-63.97	-64.45	-60.78	-44.97
EC 2 semi 86 245	-38.04	-54.27	-65.83	-70.79	-68.73	-73.73	-61.59	-64.13	-65.93	-64.35	-62.27	-51.07
EC 2 semi 91 245	-34.58	-51.77	-63.13	-69.52	-68.75	-73.91	-60.01	-62.73	-64.29	-63.18	-61.03	-49.42
EC 2 semi 96 245	-28.70	-49.19	-62.77	-66.83	-67.93	-74.05	-57.86	-61.21	-64.70	-64.77	-61.54	-45.45
EC 3 snow 96 245	-24.64	-45.44	-62.64	-65.30	-66.23	-72.29	-57.61	-60.67	-63.60	-63.32	-60.01	-42.64
EC 3 snow 01 245	-27.51	-49.38	-63.31	-67.13	-66.26	-73.16	-59.02	-61.05	-65.32	-63.50	-60.54	-45.99
EC 4 distributed 86 245	-30.54	-53.29	-63.64	-74.55	-69.21	-73.82	-63.96	-64.79	-68.14	-67.04	-63.45	-47.20
EC 4 distributed 91 245	-33.27	-51.43	-61.03	-72.79	-70.98	-74.55	-62.81	-64.84	-67.25	-66.44	-64.17	-50.56
EC 4 distributed 96 245	-35.96	-51.13	-61.83	-65.49	-68.27	-74.90	-61.03	-62.05	-67.90	-66.81	-63.00	-48.81

Continued on next page

Tab. 6.51: Changes in discharge for seasonal runoff compared to 10 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
GFDL 1 lumped 86 245	-41.81	-58.47	-72.59	-81.82	-80.11	-79.78	-64.37	-60.30	-60.53	-61.17	-56.79	-50.64
GFDL 1 lumped 91 245	-44.13	-59.84	-72.84	-79.68	-80.26	-80.16	-63.38	-59.50	-59.99	-61.11	-56.83	-51.48
GFDL 1 lumped 96 245	-41.88	-59.09	-73.01	-79.73	-79.89	-80.11	-62.83	-58.69	-60.48	-61.70	-57.06	-49.75
GFDL 2 semi 86 245	-40.83	-61.52	-75.41	-81.08	-80.23	-80.48	-64.01	-58.54	-59.80	-60.00	-55.51	-48.47
GFDL 2 semi 91 245	-39.48	-60.12	-73.73	-80.39	-80.35	-80.62	-62.76	-57.25	-58.48	-59.37	-54.84	-48.57
GFDL 2 semi 96 245	-39.79	-61.37	-75.06	-79.54	-80.29	-81.10	-61.79	-56.34	-59.15	-59.93	-55.48	-47.87
GFDL 3 snow 96 245	-38.61	-59.38	-75.30	-78.79	-79.45	-80.22	-62.57	-57.53	-59.63	-60.18	-56.54	-47.91
GFDL 3 snow 01 245	-38.12	-61.05	-75.16	-79.64	-79.33	-80.64	-63.06	-56.71	-60.01	-58.69	-55.08	-47.00
GFDL 4 distributed 86 245	-36.23	-60.91	-73.74	-83.04	-80.26	-80.76	-67.17	-60.29	-62.25	-62.29	-58.24	-46.34
GFDL 4 distributed 91 245	-41.12	-61.10	-72.37	-81.99	-81.12	-80.74	-65.25	-60.12	-60.80	-61.24	-57.59	-50.37
GFDL 4 distributed 96 245	-48.80	-63.58	-74.20	-78.35	-80.13	-81.74	-64.54	-56.73	-60.21	-59.05	-56.70	-51.67
MPI 1 lumped 86 245	-49.40	-62.91	-70.47	-80.93	-81.20	-82.82	-73.51	-71.93	-69.21	-67.85	-62.70	-56.32
MPI 1 lumped 91 245	-50.73	-63.71	-70.74	-78.74	-81.17	-83.06	-72.71	-71.19	-68.47	-67.48	-62.46	-56.94
MPI 1 lumped 96 245	-49.60	-63.83	-71.21	-79.17	-81.22	-83.29	-72.50	-70.56	-68.34	-67.72	-62.58	-55.23
MPI 2 semi 86 245	-47.88	-64.65	-73.22	-80.09	-81.16	-83.36	-73.40	-70.98	-68.72	-66.68	-61.26	-54.18
MPI 2 semi 91 245	-46.33	-63.89	-71.60	-79.28	-81.34	-83.61	-72.61	-70.10	-67.50	-66.07	-60.68	-54.01
MPI 2 semi 96 245	-47.08	-65.40	-73.35	-78.94	-81.55	-84.21	-72.08	-69.36	-67.23	-65.88	-60.87	-53.11
MPI 3 snow 96 245	-46.79	-64.12	-74.01	-78.26	-80.77	-83.40	-72.39	-69.90	-67.64	-66.34	-62.14	-53.58
MPI 3 snow 01 245	-46.14	-65.55	-74.03	-79.29	-80.69	-83.75	-72.83	-69.58	-68.29	-64.98	-60.94	-52.79
MPI 4 distributed 86 245	-44.34	-64.71	-71.92	-81.70	-80.55	-83.03	-74.84	-71.35	-69.81	-67.76	-62.86	-51.87
MPI 4 distributed 91 245	-48.56	-65.23	-70.56	-80.53	-81.54	-83.18	-73.59	-71.30	-68.73	-66.93	-62.45	-55.58
MPI 4 distributed 96 245	-55.19	-66.92	-73.37	-77.51	-80.75	-84.12	-73.40	-69.29	-67.97	-64.67	-61.50	-57.13
MRI 1 lumped 86 245	-74.99	-79.79	-82.20	-88.23	-87.12	-87.80	-81.13	-82.10	-82.73	-82.98	-82.82	-80.15
MRI 1 lumped 91 245	-75.29	-80.08	-82.58	-87.11	-87.23	-88.05	-80.66	-81.75	-82.38	-82.85	-82.68	-80.33
MRI 1 lumped 96 245	-73.85	-79.36	-82.13	-87.00	-87.07	-88.10	-80.32	-81.35	-82.48	-83.39	-83.15	-79.35
MRI 2 semi 86 245	-75.05	-81.28	-84.31	-88.02	-87.28	-88.30	-81.24	-81.88	-82.95	-83.06	-83.01	-80.11
MRI 2 semi 91 245	-74.05	-80.82	-83.45	-87.67	-87.39	-88.48	-80.69	-81.41	-82.35	-82.71	-82.67	-79.89
MRI 2 semi 96 245	-73.22	-80.54	-83.67	-87.00	-87.33	-88.80	-80.15	-81.07	-82.63	-83.40	-83.37	-79.40
MRI 3 snow 96 245	-72.19	-79.37	-83.74	-86.34	-86.73	-88.15	-80.24	-81.00	-82.29	-82.88	-82.92	-78.56
MRI 3 snow 01 245	-72.52	-80.36	-83.79	-86.92	-86.71	-88.43	-80.64	-80.99	-82.94	-82.75	-82.78	-79.05
MRI 4 distributed 86 245	-73.81	-81.13	-83.05	-88.82	-87.30	-88.56	-82.89	-82.67	-84.17	-84.58	-84.21	-79.48
MRI 4 distributed 91 245	-74.56	-80.78	-82.28	-88.31	-88.03	-88.75	-82.20	-82.66	-83.64	-84.05	-84.22	-80.61
MRI 4 distributed 96 245	-76.34	-80.62	-83.48	-86.13	-87.37	-89.26	-81.78	-81.51	-83.84	-84.10	-84.37	-80.59
TAI 1 lumped 86 245	-77.36	-81.96	-83.34	-88.18	-87.13	-89.07	-84.46	-85.78	-86.27	-85.41	-84.21	-81.99
TAI 1 lumped 91 245	-77.75	-82.24	-83.38	-86.91	-87.14	-89.22	-83.95	-85.37	-85.84	-85.13	-83.90	-81.98
TAI 1 lumped 96 245	-76.08	-81.48	-83.15	-86.93	-87.02	-89.24	-83.49	-84.77	-85.74	-85.34	-83.87	-80.64

Continued on next page

Tab. 6.51: Changes in discharge for seasonal runoff compared to 10 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
TAI 2 semi 86 245	-77.47	-83.32	-85.13	-87.81	-87.16	-89.45	-84.49	-85.56	-86.41	-85.35	-84.20	-81.82
TAI 2 semi 91 245	-76.56	-82.87	-84.23	-87.38	-87.25	-89.61	-83.99	-85.07	-85.83	-84.96	-83.77	-81.51
TAI 2 semi 96 245	-75.52	-82.55	-84.48	-86.85	-87.20	-89.87	-83.35	-84.45	-85.81	-85.15	-83.79	-80.51
TAI 3 snow 96 245	-74.46	-81.40	-84.74	-86.29	-86.67	-89.28	-83.47	-84.49	-85.60	-84.85	-83.59	-79.80
TAI 3 snow 01 245	-74.99	-82.40	-84.83	-86.93	-86.60	-89.45	-83.79	-84.40	-86.15	-84.76	-83.51	-80.30
TAI 4 distributed 86 245	-75.85	-83.06	-84.26	-88.88	-87.14	-89.37	-85.40	-85.68	-86.94	-86.12	-84.80	-80.87
TAI 4 distributed 91 245	-77.10	-83.03	-83.40	-88.23	-87.78	-89.58	-84.85	-85.64	-86.50	-85.73	-84.85	-82.12
TAI 4 distributed 96 245	-78.71	-82.94	-84.48	-86.15	-87.10	-89.92	-84.35	-84.48	-86.67	-85.42	-84.35	-81.73
CMCC 1 lumped 86 370	23.05	0.40	-16.21	-38.82	-39.51	-52.70	-34.91	-39.92	-36.80	-33.01	-26.86	-13.24
CMCC 1 lumped 91 370	24.24	-0.10	-16.73	-31.78	-39.50	-53.05	-32.29	-37.47	-33.73	-30.57	-23.79	-10.95
CMCC 1 lumped 96 370	36.83	7.35	-13.12	-29.92	-37.55	-51.38	-28.45	-34.83	-33.45	-32.60	-22.43	-2.43
CMCC 2 semi 86 370	22.92	-8.88	-26.32	-36.97	-40.14	-55.51	-36.97	-40.79	-38.08	-33.56	-27.81	-12.96
CMCC 2 semi 91 370	28.43	-4.54	-21.22	-34.56	-40.59	-55.95	-34.50	-38.48	-34.89	-31.03	-24.42	-10.54
CMCC 2 semi 96 370	40.29	0.53	-19.99	-28.71	-38.67	-55.20	-29.78	-35.42	-34.61	-32.47	-22.01	-1.56
CMCC 3 snow 96 370	45.60	7.33	-20.54	-26.07	-35.58	-51.81	-28.69	-34.12	-32.87	-30.48	-21.09	1.59
CMCC 3 snow 01 370	40.23	-0.19	-21.93	-29.61	-35.04	-53.55	-31.83	-35.49	-36.58	-31.04	-22.32	-2.72
CMCC 4 distributed 86 370	35.20	-4.45	-19.73	-42.66	-39.61	-54.07	-38.93	-39.30	-39.26	-35.58	-26.65	-2.44
CMCC 4 distributed 91 370	29.70	-3.34	-15.76	-40.36	-44.34	-56.67	-39.19	-40.88	-39.27	-35.39	-27.59	-8.10
CMCC 4 distributed 96 370	25.03	-2.67	-19.53	-26.08	-38.80	-56.93	-36.95	-37.89	-40.72	-34.75	-21.82	0.45
EC 1 lumped 86 370	-18.59	-37.89	-59.92	-72.18	-67.69	-70.23	-58.85	-61.86	-60.53	-56.46	-48.58	-35.24
EC 1 lumped 91 370	-19.68	-39.22	-59.49	-68.35	-67.63	-70.52	-57.42	-60.62	-59.13	-55.55	-47.72	-35.10
EC 1 lumped 96 370	-12.09	-35.40	-58.71	-67.95	-66.66	-70.08	-56.03	-59.21	-58.96	-56.06	-46.29	-28.35
EC 2 semi 86 370	-19.21	-43.46	-64.44	-71.09	-67.81	-71.19	-59.06	-61.58	-60.99	-56.32	-48.43	-34.36
EC 2 semi 91 370	-14.48	-40.17	-61.37	-69.75	-67.75	-71.26	-57.29	-59.95	-58.96	-54.75	-46.68	-32.21
EC 2 semi 96 370	-8.77	-39.03	-62.15	-67.84	-67.19	-71.66	-55.63	-58.79	-59.23	-55.21	-45.38	-26.57
EC 3 snow 96 370	-5.58	-35.92	-61.89	-66.37	-65.75	-70.15	-55.82	-58.45	-58.45	-54.42	-45.17	-25.11
EC 3 snow 01 370	-7.34	-40.17	-62.47	-68.30	-65.88	-71.02	-57.04	-58.85	-60.47	-54.48	-45.10	-27.33
EC 4 distributed 86 370	-11.16	-42.74	-62.91	-74.96	-68.38	-71.47	-61.61	-61.91	-62.76	-58.57	-49.97	-29.98
EC 4 distributed 91 370	-15.39	-41.30	-60.21	-73.46	-70.03	-71.71	-59.98	-61.63	-61.41	-57.32	-49.73	-34.37
EC 4 distributed 96 370	-22.04	-43.42	-60.78	-66.29	-67.55	-72.40	-58.50	-59.06	-61.84	-55.56	-46.70	-33.54
GFDL 1 lumped 86 370	-43.51	-56.68	-68.73	-78.74	-77.98	-79.20	-66.64	-66.36	-68.57	-68.27	-65.09	-57.80
GFDL 1 lumped 91 370	-45.22	-57.64	-68.77	-76.09	-77.99	-79.52	-65.73	-65.60	-67.89	-67.91	-64.66	-57.95
GFDL 1 lumped 96 370	-41.89	-56.42	-68.69	-76.03	-77.56	-79.52	-65.32	-65.09	-68.51	-68.86	-64.88	-55.59
GFDL 2 semi 86 370	-43.18	-60.13	-71.97	-77.85	-78.13	-80.00	-66.74	-65.52	-68.69	-68.08	-64.81	-56.58
GFDL 2 semi 91 370	-41.38	-58.37	-69.98	-76.98	-78.26	-80.26	-65.80	-64.59	-67.59	-67.34	-63.89	-56.21
GFDL 2 semi 96 370	-39.98	-58.79	-71.11	-75.76	-78.08	-80.82	-65.14	-64.17	-68.54	-68.44	-64.25	-54.45

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Tab. 6.51: Changes in discharge for seasonal runoff compared to 10 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
GFDL 3 snow 96 370	-38.49	-56.59	-71.33	-74.86	-77.01	-79.70	-65.28	-64.40	-68.12	-67.87	-64.39	-53.83
GFDL 3 snow 01 370	-38.96	-58.88	-71.40	-75.94	-76.89	-80.27	-66.01	-64.20	-69.03	-67.49	-63.83	-54.00
GFDL 4 distributed 86 370	-38.19	-59.61	-70.43	-80.34	-77.95	-79.96	-68.99	-66.28	-70.50	-70.40	-66.89	-54.48
GFDL 4 distributed 91 370	-42.65	-59.54	-68.87	-79.16	-79.20	-80.35	-67.82	-66.53	-69.65	-69.46	-66.46	-57.66
GFDL 4 distributed 96 370	-49.05	-61.43	-70.52	-74.48	-77.71	-81.26	-67.55	-64.47	-70.26	-69.17	-65.80	-57.71
MPI 1 lumped 86 370	-54.30	-63.81	-72.94	-82.85	-82.02	-83.16	-74.43	-75.74	-76.42	-75.81	-73.07	-67.32
MPI 1 lumped 91 370	-55.50	-64.63	-73.19	-80.85	-82.02	-83.39	-73.68	-75.12	-75.79	-75.48	-72.77	-67.42
MPI 1 lumped 96 370	-53.32	-63.94	-73.34	-81.02	-81.91	-83.54	-73.37	-74.60	-76.04	-76.22	-73.14	-65.96
MPI 2 semi 86 370	-53.84	-66.25	-75.74	-82.18	-82.07	-83.73	-74.45	-75.25	-76.53	-75.63	-72.87	-66.55
MPI 2 semi 91 370	-52.44	-65.26	-74.20	-81.51	-82.22	-83.98	-73.72	-74.56	-75.67	-75.11	-72.33	-66.31
MPI 2 semi 96 370	-51.66	-65.77	-75.46	-80.93	-82.25	-84.48	-73.13	-74.09	-76.07	-75.86	-72.85	-65.25
MPI 3 snow 96 370	-50.66	-64.04	-75.82	-80.11	-81.46	-83.63	-73.31	-74.16	-75.77	-75.45	-72.79	-64.71
MPI 3 snow 01 370	-51.08	-65.77	-75.99	-81.12	-81.48	-84.03	-73.80	-74.04	-76.59	-75.16	-72.46	-65.01
MPI 4 distributed 86 370	-50.65	-65.96	-74.24	-83.63	-81.75	-83.77	-76.17	-75.70	-77.62	-77.07	-74.05	-64.55
MPI 4 distributed 91 370	-53.77	-66.25	-72.96	-82.70	-82.85	-84.05	-75.22	-75.80	-76.93	-76.40	-73.87	-66.95
MPI 4 distributed 96 370	-58.83	-67.60	-75.15	-79.55	-81.83	-84.73	-74.79	-74.26	-77.33	-76.15	-73.58	-67.18
MRI 1 lumped 86 370	-66.36	-73.88	-79.03	-85.61	-83.82	-84.68	-75.99	-76.73	-79.48	-80.91	-80.04	-74.08
MRI 1 lumped 91 370	-67.12	-74.44	-79.32	-84.01	-83.87	-84.94	-75.40	-76.31	-79.10	-80.77	-79.93	-74.39
MRI 1 lumped 96 370	-65.51	-73.93	-79.33	-84.15	-83.86	-85.13	-75.24	-75.88	-79.35	-81.46	-80.55	-73.11
MRI 2 semi 86 370	-65.88	-75.54	-81.31	-85.07	-83.82	-85.08	-75.66	-75.96	-79.49	-80.83	-79.99	-73.43
MRI 2 semi 91 370	-64.77	-74.92	-80.19	-84.56	-83.94	-85.30	-75.01	-75.39	-78.85	-80.48	-79.66	-73.28
MRI 2 semi 96 370	-64.08	-75.23	-81.02	-84.04	-84.05	-85.81	-74.58	-75.00	-79.33	-81.41	-80.58	-72.53
MRI 3 snow 96 370	-63.35	-73.92	-81.26	-83.41	-83.44	-85.18	-75.12	-75.38	-79.15	-81.00	-80.38	-72.09
MRI 3 snow 01 370	-63.23	-74.92	-81.26	-84.17	-83.26	-85.33	-75.25	-74.94	-79.61	-80.64	-80.06	-72.23
MRI 4 distributed 86 370	-63.89	-75.51	-80.18	-86.47	-83.91	-85.33	-77.75	-76.66	-80.33	-82.00	-81.12	-72.36
MRI 4 distributed 91 370	-65.95	-75.65	-79.27	-85.69	-84.73	-85.45	-76.72	-76.76	-79.71	-81.47	-81.13	-74.17
MRI 4 distributed 96 370	-69.21	-76.29	-80.93	-83.13	-83.87	-86.00	-76.21	-75.04	-80.05	-81.82	-81.60	-74.44
TAI 1 lumped 86 370	-70.07	-76.02	-79.24	-87.25	-89.09	-91.52	-87.34	-87.28	-86.62	-84.73	-81.48	-76.71
TAI 1 lumped 91 370	-70.13	-76.14	-79.26	-85.78	-89.09	-91.59	-86.78	-86.75	-86.05	-84.26	-80.77	-76.21
TAI 1 lumped 96 370	-68.21	-75.54	-79.34	-86.02	-88.95	-91.38	-86.23	-86.11	-85.88	-84.11	-79.91	-73.96
TAI 2 semi 86 370	-69.47	-77.37	-81.29	-86.77	-89.24	-92.03	-87.66	-87.27	-86.85	-84.68	-81.17	-75.80
TAI 2 semi 91 370	-68.18	-76.73	-80.15	-86.27	-89.38	-92.11	-87.16	-86.71	-86.18	-84.12	-80.29	-75.15
TAI 2 semi 96 370	-66.75	-76.64	-80.93	-85.98	-89.33	-92.11	-86.44	-85.90	-85.88	-83.66	-79.08	-72.81
TAI 3 snow 96 370	-66.07	-75.44	-81.33	-85.39	-88.72	-91.52	-86.30	-85.88	-85.75	-83.51	-79.46	-72.56
TAI 3 snow 01 370	-66.56	-76.74	-81.58	-86.18	-88.78	-91.89	-86.88	-85.91	-86.24	-83.35	-79.39	-72.95
TAI 4 distributed 86 370	-67.62	-77.29	-80.35	-87.60	-88.28	-91.16	-87.69	-86.90	-87.22	-85.41	-81.94	-74.65

Continued on next page

Tab. 6.51: Changes in discharge for seasonal runoff compared to 10 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
TAI 4 distributed 91 370	-70.07	-77.89	-79.53	-87.01	-89.18	-91.54	-87.36	-86.88	-86.78	-85.03	-81.97	-76.76
TAI 4 distributed 96 370	-72.37	-78.06	-81.30	-85.05	-88.74	-92.06	-87.35	-86.06	-86.95	-84.17	-80.19	-75.32
CMCC 1 lumped 86 585	54.87	11.56	-11.02	-37.04	-36.95	-47.04	-26.44	-33.46	-29.59	-23.39	-5.61	18.74
CMCC 1 lumped 91 585	54.50	10.19	-11.80	-30.28	-37.00	-47.68	-23.97	-31.25	-26.62	-20.92	-2.65	20.86
CMCC 1 lumped 96 585	66.05	15.16	-10.16	-29.71	-36.07	-47.31	-21.53	-29.66	-26.84	-23.17	-0.47	31.26
CMCC 2 semi 86 585	56.63	2.94	-21.41	-35.48	-37.68	-49.81	-28.40	-34.37	-30.94	-23.75	-6.00	20.84
CMCC 2 semi 91 585	62.06	6.25	-16.48	-33.35	-38.33	-50.58	-26.06	-32.17	-27.65	-21.14	-2.59	23.01
CMCC 2 semi 96 585	71.93	8.38	-17.81	-29.24	-37.53	-51.19	-22.79	-30.47	-28.10	-22.72	0.81	34.38
CMCC 3 snow 96 585	76.44	15.24	-18.47	-26.19	-34.33	-47.83	-21.73	-28.89	-26.25	-20.62	1.36	37.17
CMCC 3 snow 01 585	73.43	8.53	-19.73	-30.06	-34.36	-49.57	-24.58	-29.87	-30.15	-21.21	0.18	33.52
CMCC 4 distributed 86 585	68.43	6.57	-14.92	-40.08	-35.91	-48.22	-31.61	-34.59	-34.15	-27.21	-6.52	32.80
CMCC 4 distributed 91 585	59.22	5.57	-11.39	-37.92	-40.94	-50.71	-31.00	-35.41	-33.10	-26.22	-6.96	23.25
CMCC 4 distributed 96 585	48.40	4.80	-17.70	-26.24	-37.32	-52.86	-30.21	-33.45	-35.57	-25.21	0.56	31.59
EC 1 lumped 86 585	-35.02	-46.17	-63.14	-74.45	-72.48	-74.01	-59.45	-60.41	-62.76	-62.71	-61.66	-52.78
EC 1 lumped 91 585	-35.52	-47.28	-62.85	-71.04	-72.53	-74.30	-57.92	-59.09	-61.52	-61.92	-60.81	-52.47
EC 1 lumped 96 585	-28.15	-42.71	-61.33	-70.21	-71.26	-73.45	-55.96	-56.88	-60.95	-62.56	-60.85	-47.82
EC 2 semi 86 585	-36.36	-51.69	-67.64	-73.68	-72.95	-75.31	-59.92	-59.91	-63.26	-62.74	-62.05	-52.90
EC 2 semi 91 585	-32.54	-48.90	-64.86	-72.49	-72.94	-75.29	-58.13	-58.18	-61.51	-61.53	-60.72	-51.31
EC 2 semi 96 585	-26.48	-46.40	-64.65	-70.14	-72.07	-75.17	-55.60	-55.82	-61.18	-62.41	-61.13	-47.90
EC 3 snow 96 585	-22.63	-42.90	-64.17	-68.59	-70.41	-73.54	-55.57	-55.78	-60.33	-61.26	-60.05	-45.50
EC 3 snow 01 585	-25.18	-47.00	-64.63	-70.12	-70.43	-74.42	-56.96	-55.92	-61.98	-61.17	-60.16	-48.20
EC 4 distributed 86 585	-28.91	-50.67	-66.09	-77.19	-73.56	-75.92	-63.51	-60.92	-65.15	-65.22	-63.18	-49.17
EC 4 distributed 91 585	-31.88	-48.65	-63.23	-75.67	-74.90	-76.18	-61.76	-60.55	-63.85	-64.14	-63.66	-52.62
EC 4 distributed 96 585	-34.83	-49.33	-63.08	-68.46	-72.29	-76.33	-59.29	-56.08	-63.18	-63.34	-62.45	-51.34
GFDL 1 lumped 86 585	-30.22	-47.39	-58.72	-74.10	-73.22	-73.33	-57.45	-56.81	-59.56	-59.90	-53.01	-42.39
GFDL 1 lumped 91 585	-31.20	-48.97	-59.35	-71.16	-73.30	-73.82	-56.31	-55.93	-58.89	-59.58	-52.77	-42.83
GFDL 1 lumped 96 585	-30.31	-49.13	-60.19	-71.93	-73.38	-74.17	-56.13	-55.34	-59.58	-60.40	-53.00	-41.32
GFDL 2 semi 86 585	-27.11	-49.92	-62.73	-73.13	-73.30	-74.10	-56.87	-55.08	-59.09	-58.94	-51.64	-39.58
GFDL 2 semi 91 585	-25.76	-49.35	-60.75	-72.02	-73.57	-74.51	-55.77	-54.02	-57.96	-58.40	-50.91	-39.67
GFDL 2 semi 96 585	-26.68	-51.47	-63.26	-71.72	-73.90	-75.45	-55.08	-53.41	-58.92	-59.23	-51.44	-38.67
GFDL 3 snow 96 585	-26.01	-49.30	-64.09	-70.86	-72.82	-74.34	-55.95	-54.38	-59.01	-59.15	-52.51	-38.84
GFDL 3 snow 01 585	-24.17	-51.11	-64.05	-72.14	-72.55	-74.64	-56.06	-53.21	-59.41	-57.77	-50.99	-37.61
GFDL 4 distributed 86 585	-23.90	-49.68	-60.68	-75.02	-72.67	-74.14	-59.99	-56.15	-60.83	-60.55	-54.46	-37.22
GFDL 4 distributed 91 585	-30.39	-51.53	-59.03	-73.31	-73.74	-73.97	-57.73	-56.10	-59.44	-59.67	-53.97	-42.75
GFDL 4 distributed 96 585	-39.07	-53.94	-63.42	-69.73	-72.75	-75.28	-57.11	-53.07	-59.93	-58.69	-53.27	-43.69
MPI 1 lumped 86 585	-58.19	-67.60	-73.83	-81.40	-78.49	-79.10	-71.86	-76.79	-78.47	-77.60	-75.37	-69.49

Continued on next page

Tab. 6.51: Changes in discharge for seasonal runoff compared to 10 years historical period [%] (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10	11	12
MPI 1 lumped 91 585	-59.10	-68.07	-73.97	-79.26	-78.39	-79.33	-71.14	-76.26	-77.88	-77.25	-75.01	-69.56
MPI 1 lumped 96 585	-56.63	-67.20	-73.70	-79.27	-78.30	-79.70	-70.99	-75.74	-77.99	-77.94	-75.28	-67.73
MPI 2 semi 86 585	-58.00	-69.78	-76.55	-80.65	-78.31	-79.43	-71.55	-76.44	-78.66	-77.52	-75.32	-68.96
MPI 2 semi 91 585	-56.47	-68.79	-74.99	-79.83	-78.37	-79.70	-70.88	-75.88	-77.84	-76.98	-74.74	-68.64
MPI 2 semi 96 585	-55.07	-68.81	-75.72	-78.97	-78.39	-80.44	-70.42	-75.51	-78.24	-77.80	-75.17	-67.24
MPI 3 snow 96 585	-54.00	-67.23	-76.15	-78.29	-77.74	-79.69	-70.85	-75.42	-77.89	-77.36	-74.96	-66.51
MPI 3 snow 01 585	-54.46	-68.81	-76.23	-79.39	-77.57	-79.85	-70.91	-75.26	-78.70	-77.16	-74.78	-67.03
MPI 4 distributed 86 585	-54.66	-69.40	-74.96	-82.39	-78.42	-79.85	-73.37	-76.34	-79.08	-78.34	-75.82	-66.71
MPI 4 distributed 91 585	-57.14	-69.26	-73.67	-81.32	-79.38	-80.02	-72.44	-76.53	-78.57	-77.86	-75.86	-68.94
MPI 4 distributed 96 585	-61.05	-69.90	-75.50	-77.78	-78.14	-80.60	-71.67	-75.15	-79.38	-78.21	-75.67	-68.79
MRI 1 lumped 86 585	-71.74	-78.38	-83.87	-89.06	-87.74	-88.90	-82.88	-82.52	-81.52	-82.52	-81.52	-77.15
MRI 1 lumped 91 585	-72.30	-78.84	-84.13	-87.85	-87.83	-89.08	-82.37	-82.08	-81.85	-82.31	-81.32	-77.34
MRI 1 lumped 96 585	-70.39	-77.96	-83.86	-87.76	-87.61	-88.98	-81.91	-81.59	-81.77	-82.60	-81.49	-75.66
MRI 2 semi 86 585	-71.72	-80.06	-85.77	-88.77	-87.86	-89.36	-83.00	-82.24	-82.42	-82.42	-81.47	-76.75
MRI 2 semi 91 585	-70.59	-79.42	-84.87	-88.38	-87.94	-89.45	-82.37	-81.65	-81.68	-81.95	-81.01	-76.40
MRI 2 semi 96 585	-69.44	-79.28	-85.24	-87.74	-87.82	-89.62	-81.71	-81.15	-81.63	-82.26	-81.30	-75.16
MRI 3 snow 96 585	-68.49	-77.95	-85.31	-87.17	-87.28	-89.03	-81.83	-81.19	-81.45	-81.94	-81.15	-74.65
MRI 3 snow 01 585	-68.74	-79.00	-85.41	-87.77	-87.25	-89.29	-82.25	-81.25	-82.08	-81.69	-80.93	-75.09
MRI 4 distributed 86 585	-69.67	-79.75	-84.56	-89.77	-87.91	-89.41	-84.38	-82.87	-83.48	-83.79	-82.62	-75.75
MRI 4 distributed 91 585	-71.07	-79.58	-83.78	-89.23	-88.59	-89.59	-83.69	-82.80	-82.88	-83.17	-82.61	-77.23
MRI 4 distributed 96 585	-73.20	-79.82	-84.82	-87.02	-87.87	-89.98	-83.25	-81.54	-82.59	-82.51	-82.16	-76.88
TAI 1 lumped 86 585	-69.47	-73.33	-76.99	-85.51	-86.04	-88.34	-83.34	-84.98	-85.17	-84.19	-82.78	-77.64
TAI 1 lumped 91 585	-69.40	-73.33	-76.88	-83.69	-86.03	-88.55	-82.84	-84.54	-84.67	-83.77	-82.16	-77.28
TAI 1 lumped 96 585	-67.04	-72.64	-77.03	-84.11	-86.07	-88.62	-82.39	-83.91	-84.58	-83.92	-81.61	-74.83
TAI 2 semi 86 585	-68.21	-74.39	-79.05	-84.81	-86.07	-88.81	-83.48	-84.86	-85.36	-84.09	-82.40	-76.46
TAI 2 semi 91 585	-66.57	-73.58	-77.73	-84.15	-86.24	-89.05	-83.02	-84.37	-84.72	-83.56	-81.52	-75.63
TAI 2 semi 96 585	-64.64	-73.38	-78.61	-83.97	-86.42	-89.39	-82.41	-83.76	-84.69	-83.60	-80.76	-73.18
TAI 3 snow 96 585	-64.56	-72.32	-79.29	-83.48	-85.78	-88.76	-82.48	-83.73	-84.51	-83.41	-81.22	-73.25
TAI 3 snow 01 585	-64.85	-73.59	-79.36	-84.35	-85.73	-89.01	-82.88	-83.71	-85.08	-83.18	-80.99	-73.54
TAI 4 distributed 86 585	-66.39	-74.75	-78.26	-86.04	-85.31	-88.13	-83.72	-84.33	-85.54	-84.74	-83.24	-75.64
TAI 4 distributed 91 585	-69.28	-75.44	-77.18	-85.09	-86.12	-88.37	-83.11	-84.31	-85.08	-84.32	-83.22	-77.77
TAI 4 distributed 96 585	-71.10	-75.33	-79.11	-82.91	-85.68	-89.09	-83.06	-83.53	-85.60	-84.12	-82.21	-76.58

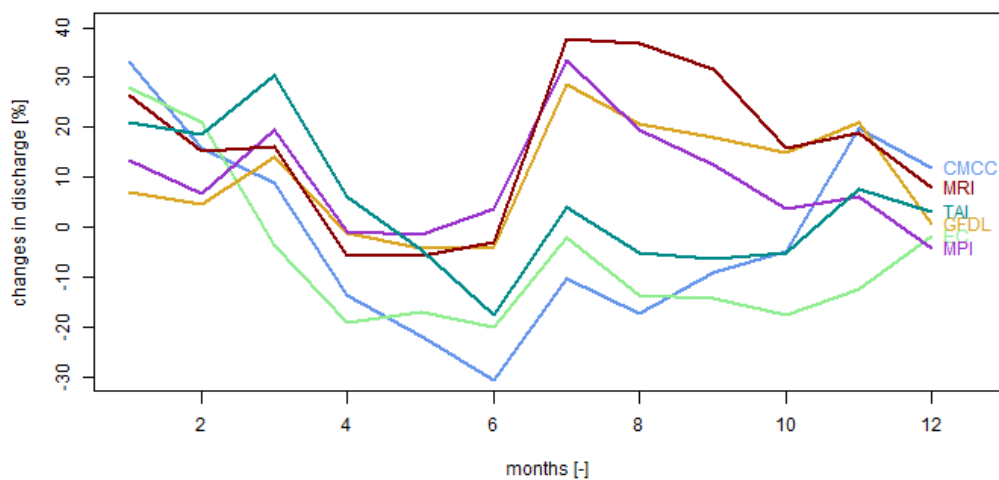


Fig. 6.1: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the lumped calibration variant in the period 1996-2005 and a 30 year historical period for reference.

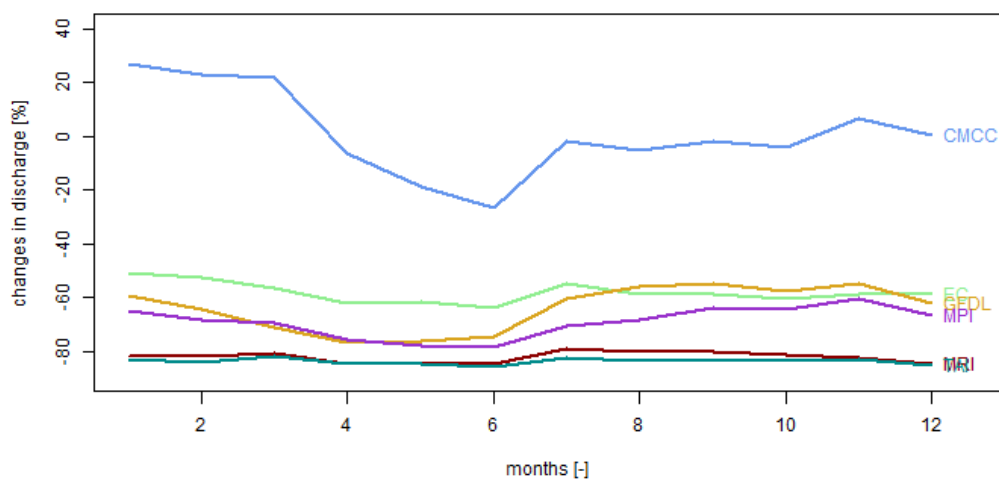


Fig. 6.2: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the lumped calibration variant in the period 1996-2005 and a 30 year historical period for reference.

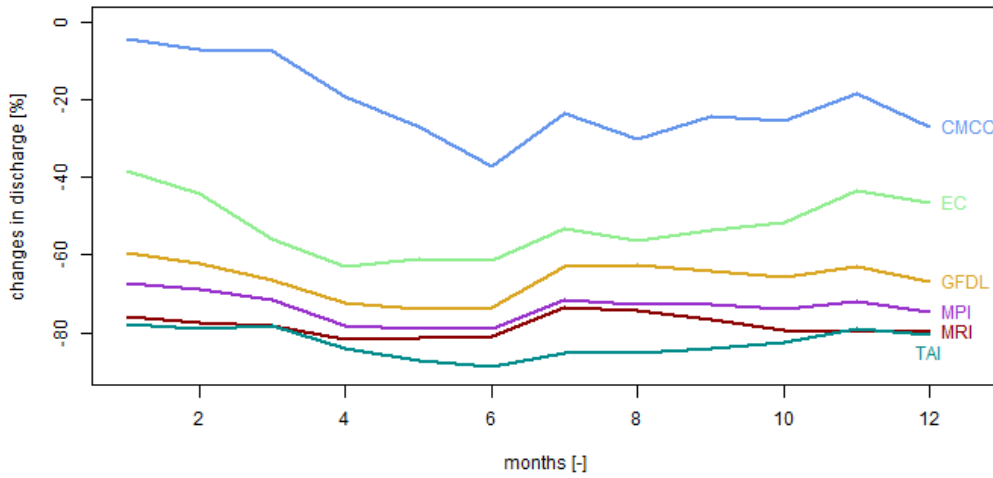


Fig. 6.3: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the lumped calibration variant in the period 1996-2005 and a 30 year historical period for reference.

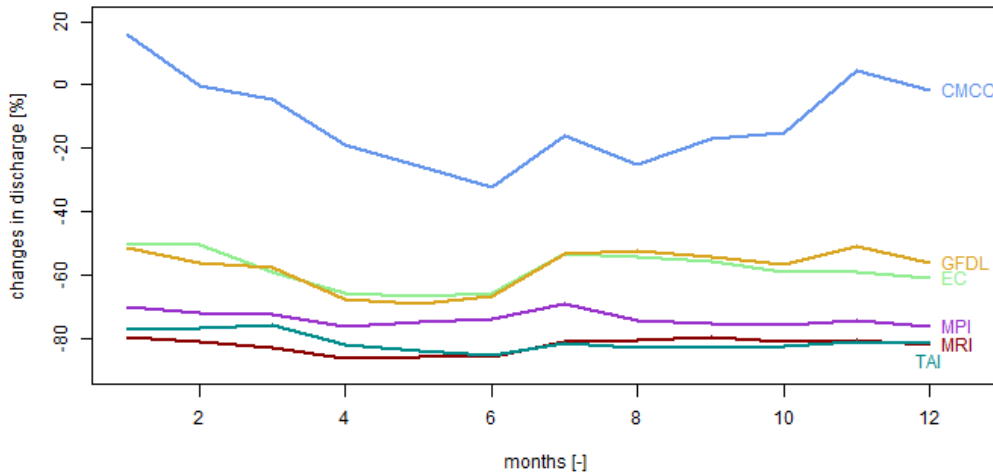


Fig. 6.4: Projections of seasonal runoff change estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the lumped calibration variant in the period 1996-2005 and a 30 year historical period for reference.

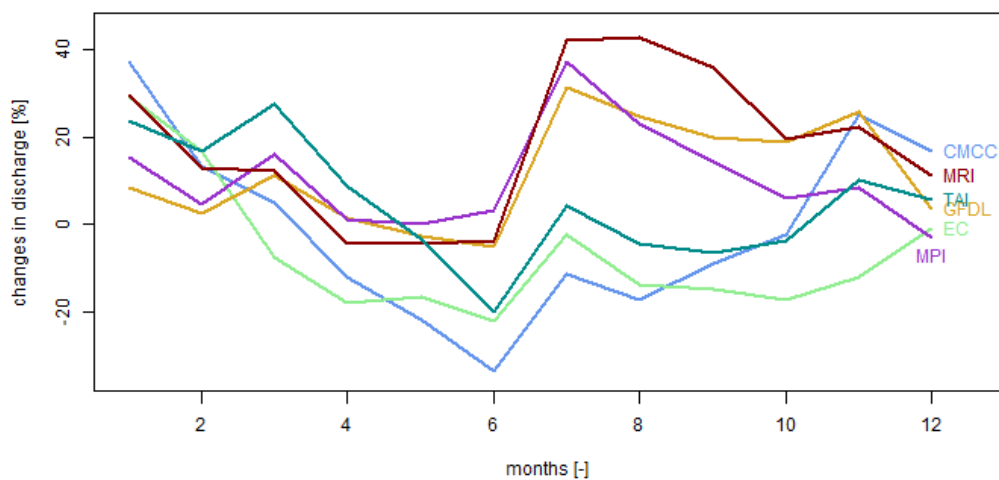


Fig. 6.5: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the semi-distributed calibration variant in the period 1996-2005 and a 30 year historical period for reference.

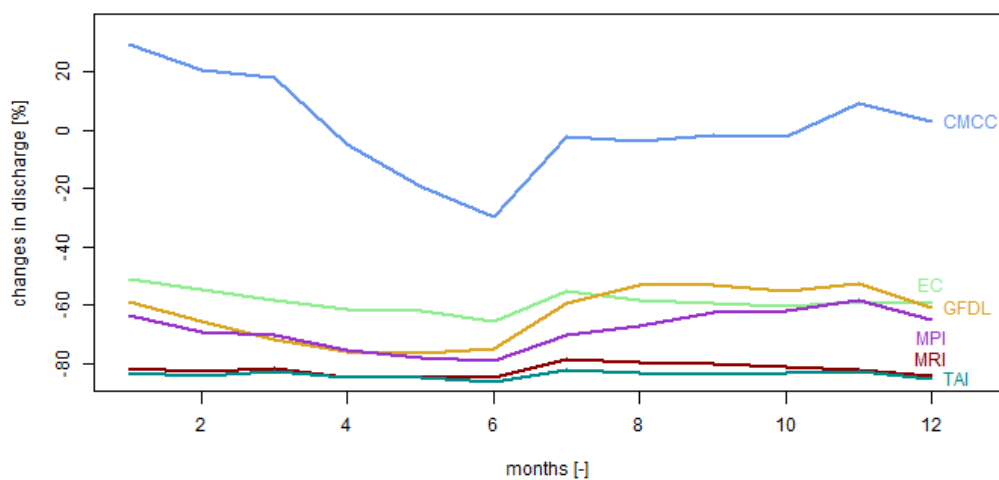


Fig. 6.6: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the semi-distributed calibration variant in the period 1996-2005 and a 30 year historical period for reference.

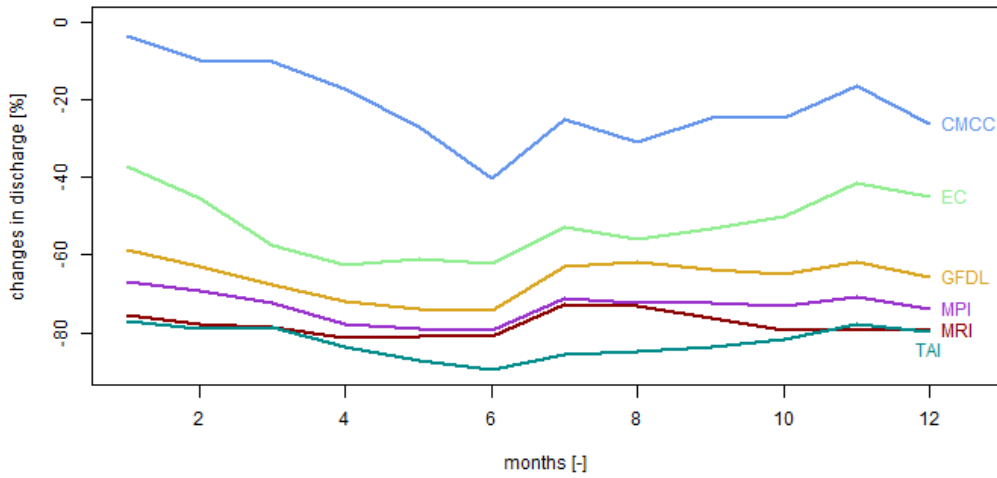


Fig. 6.7: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the semi-distributed calibration variant in the period 1996-2005 and a 30 year historical period for reference.

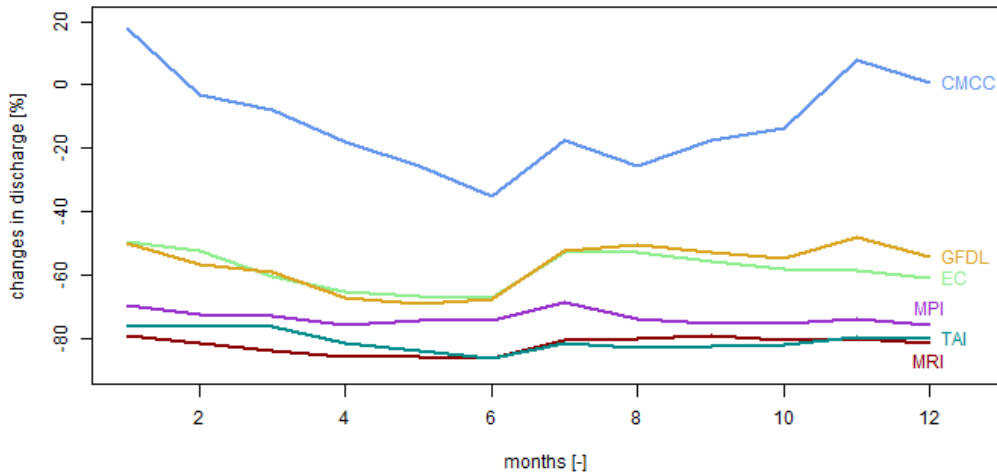


Fig. 6.8: Projections of seasonal runoff change estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the semi-distributed calibration variant in the period 1996-2005 and a 30 year historical period for reference.

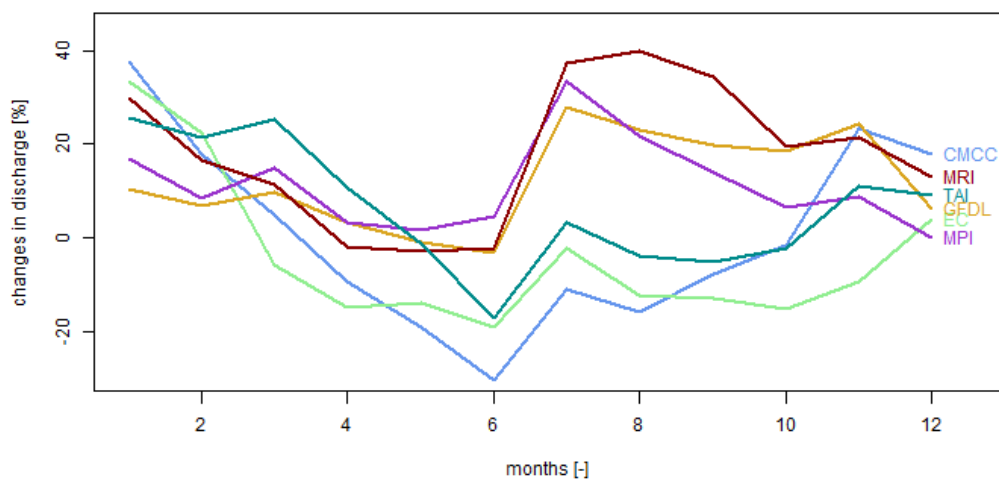


Fig. 6.9: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the snow calibration variant in the period 1996-2005 and a 30 year historical period for reference.

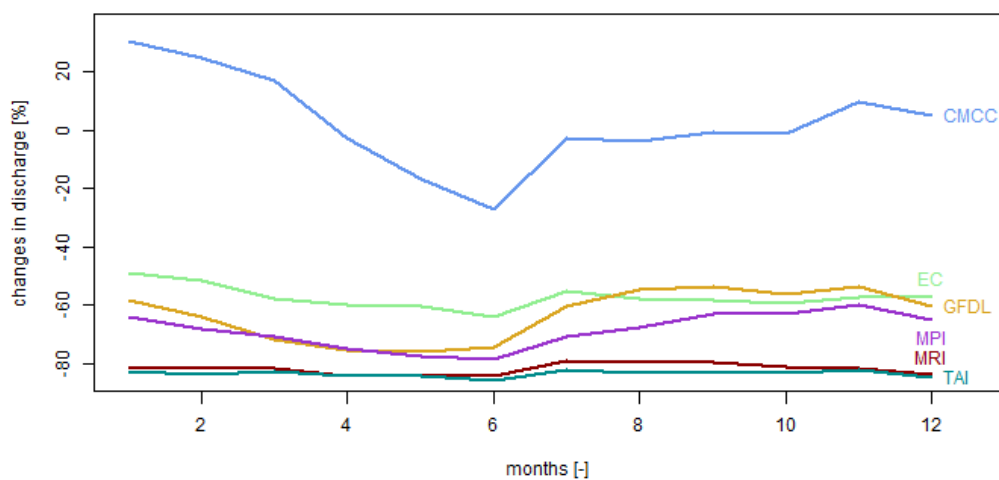


Fig. 6.10: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the snow calibration variant in the period 1996-2005 and a 30 year historical period for reference.

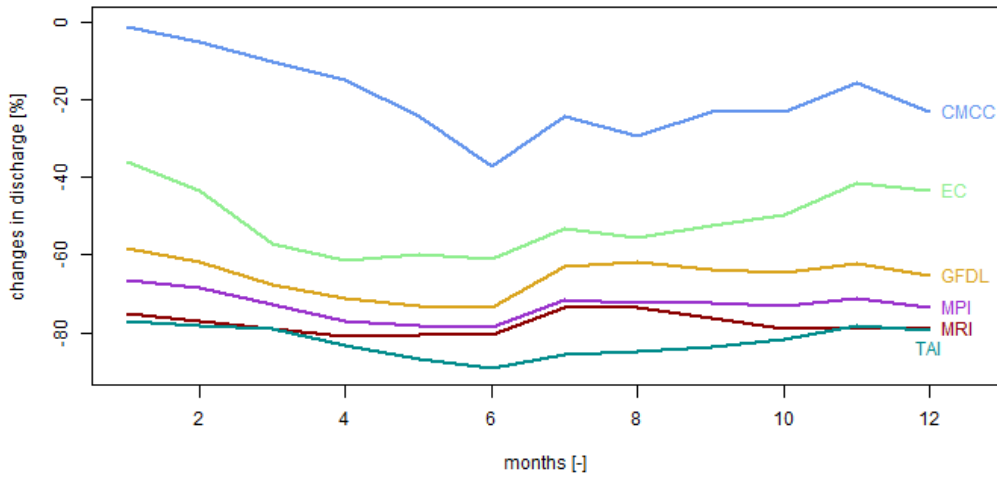


Fig. 6.11: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the snow calibration variant in the period 1996-2005 and a 30 year historical period for reference.

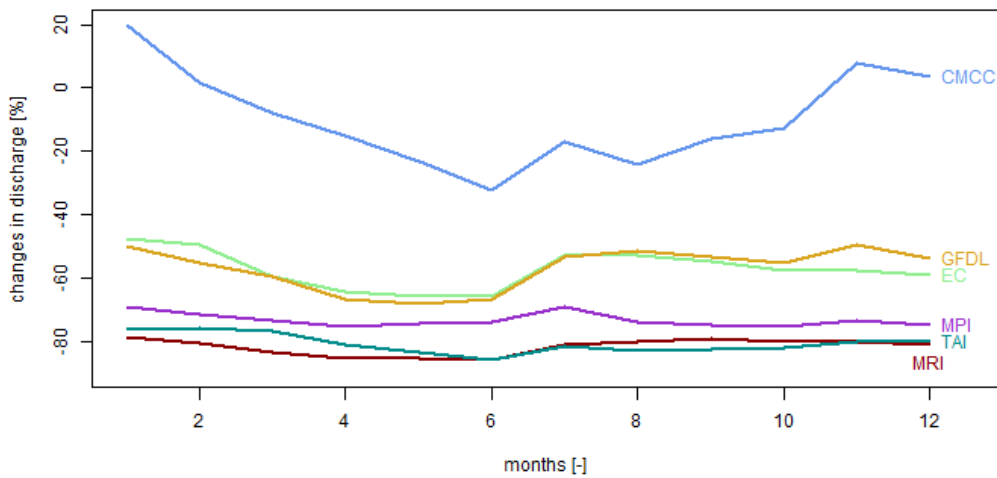


Fig. 6.12: Projections of seasonal runoff change estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the snow calibration variant in the period 1996-2005 and a 30 year historical period for reference.

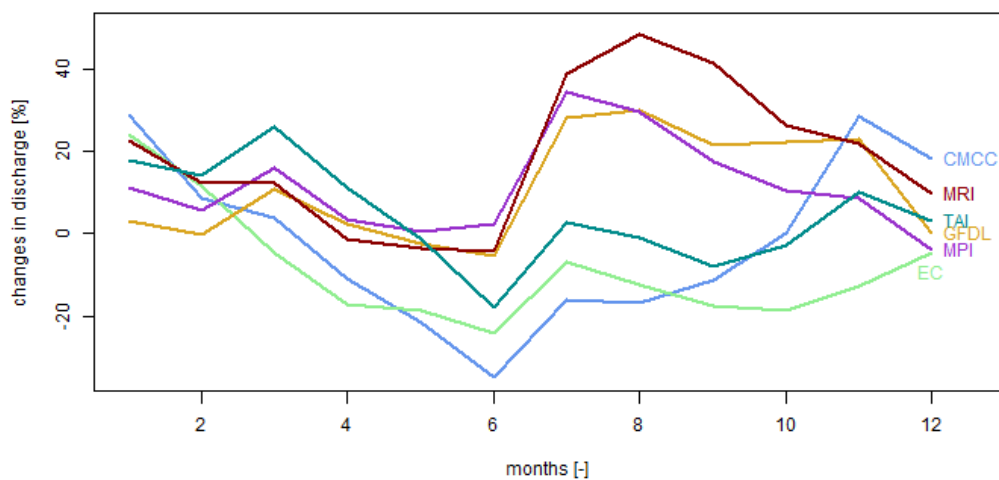


Fig. 6.13: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1996-2005 and a 30 year historical period for reference.

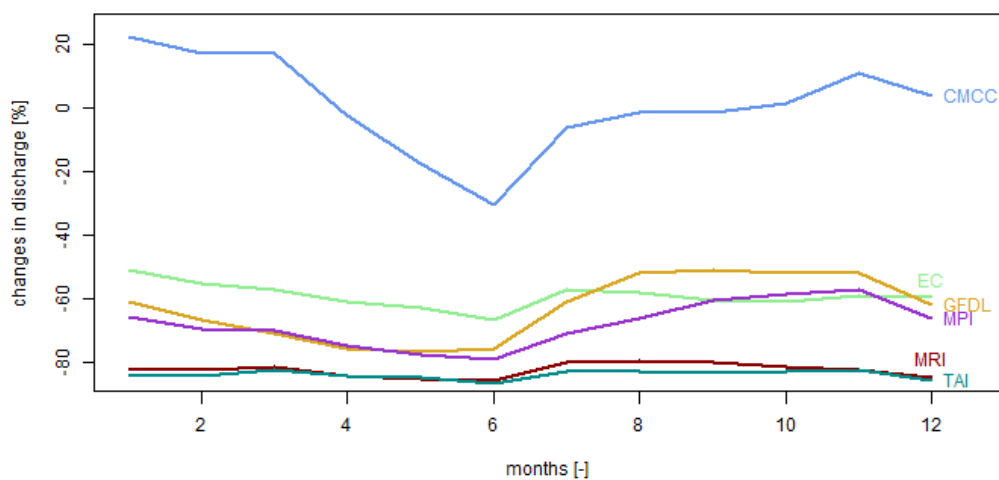


Fig. 6.14: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1996-2005 and a 30 year historical period for reference.

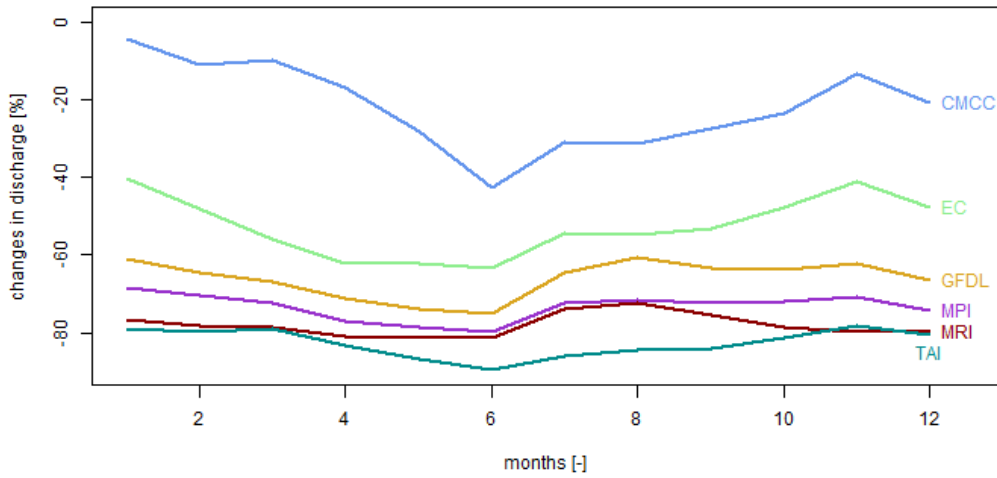


Fig. 6.15: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1996-2005 and a 30 year historical period for reference.

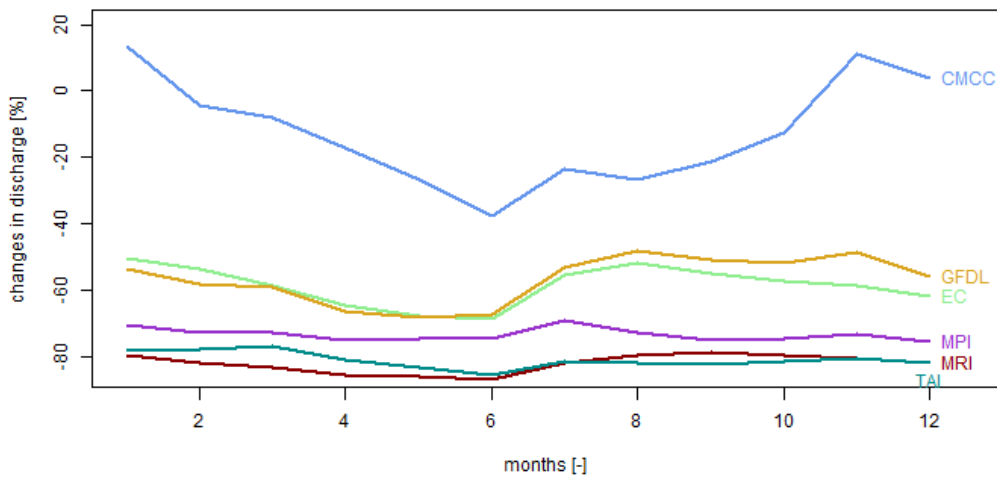


Fig. 6.16: Projections of seasonal runoff change estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1996-2005 and a 30 year historical period for reference.

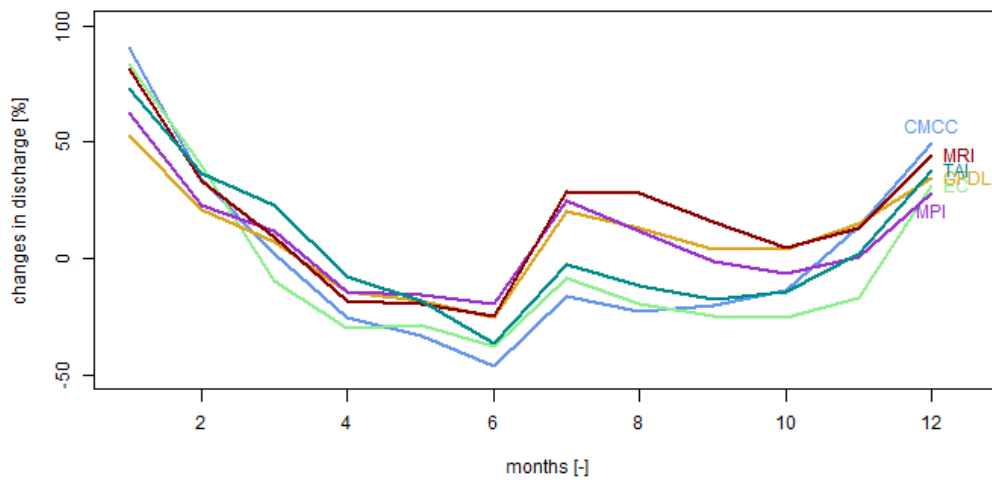


Fig. 6.17: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the lumped calibration variant in the period 1996-2005 and a 10 year historical period for reference.

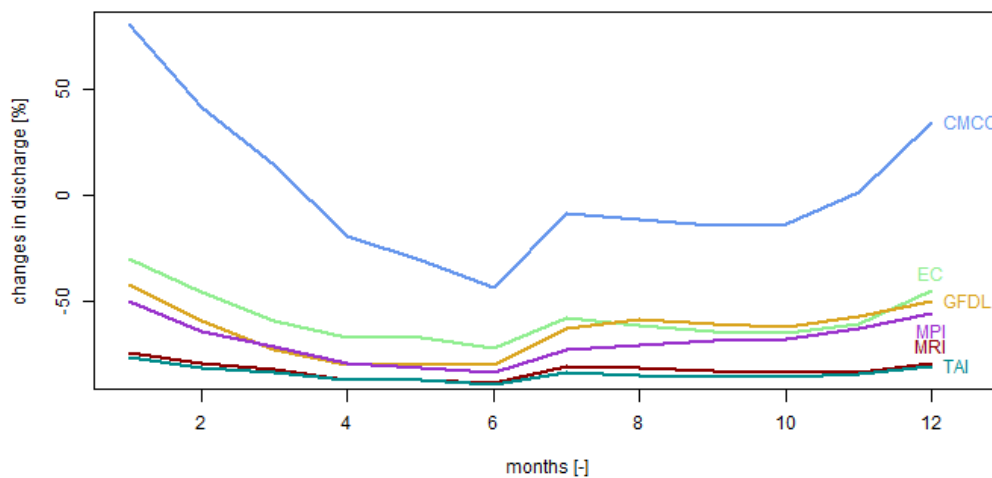


Fig. 6.18: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the lumped calibration variant in the period 1996-2005 and a 10 year historical period for reference.

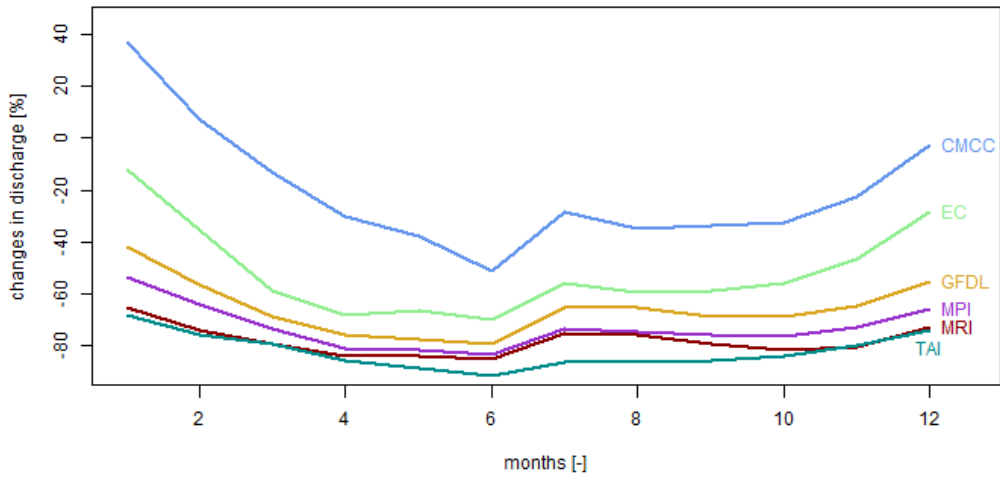


Fig. 6.19: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the lumped calibration variant in the period 1996-2005 and a 10 year historical period for reference.

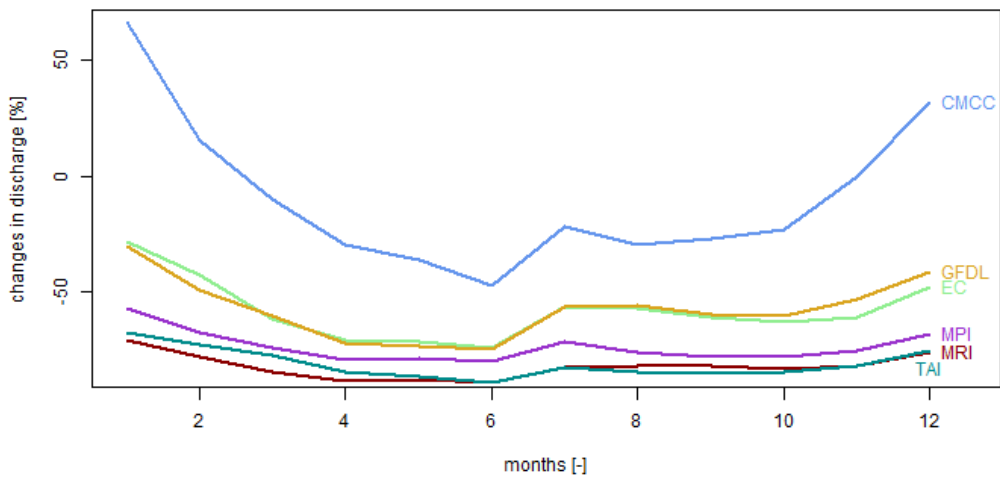


Fig. 6.20: Projections of seasonal runoff change estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the lumped calibration variant in the period 1996-2005 and a 10 year historical period for reference.

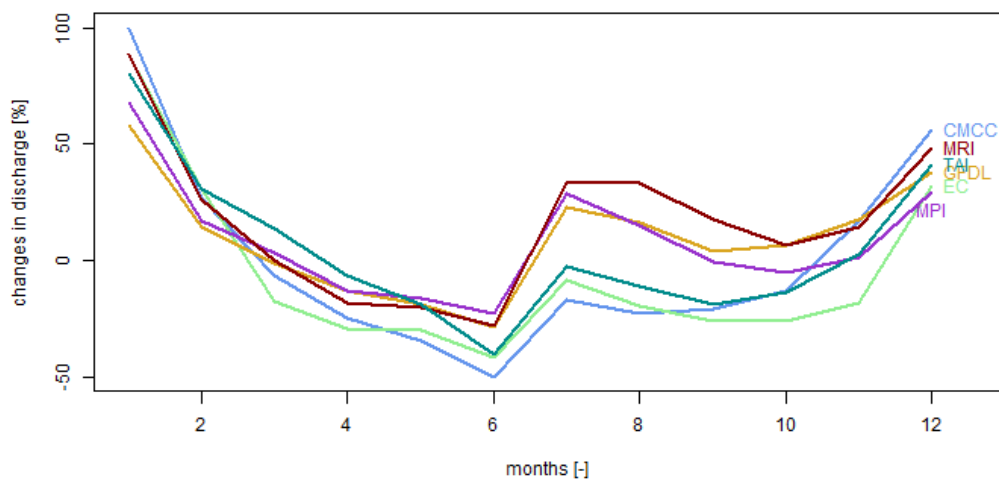


Fig. 6.21: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the semi-distributed calibration variant in the period 1996-2005 and a 10 year historical period for reference.

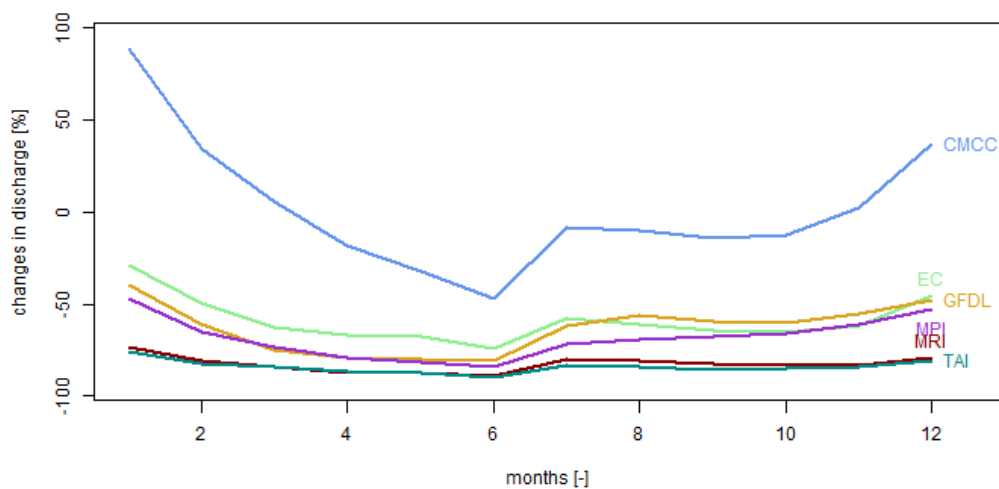


Fig. 6.22: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the semi-distributed calibration variant in the period 1996-2005 and a 10 year historical period for reference.

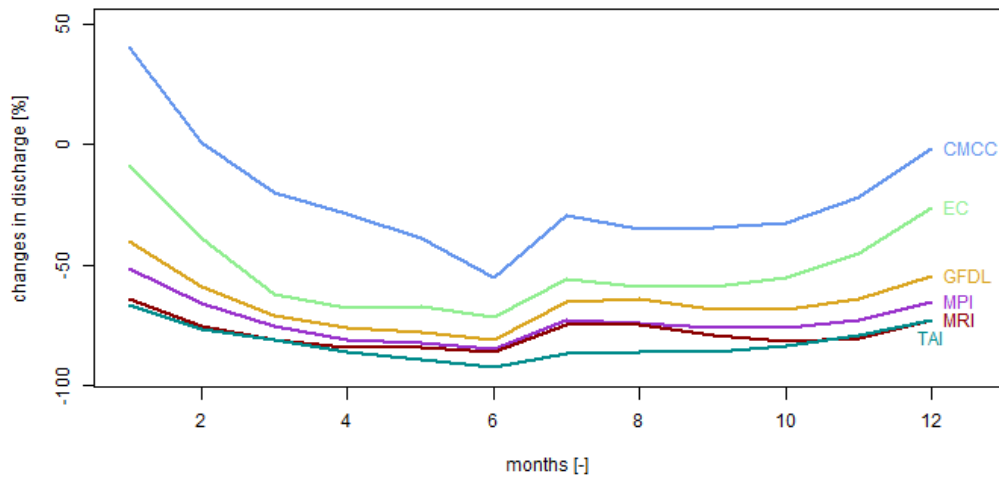


Fig. 6.23: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the semi-distributed calibration variant in the period 1996-2005 and a 10 year historical period for reference.

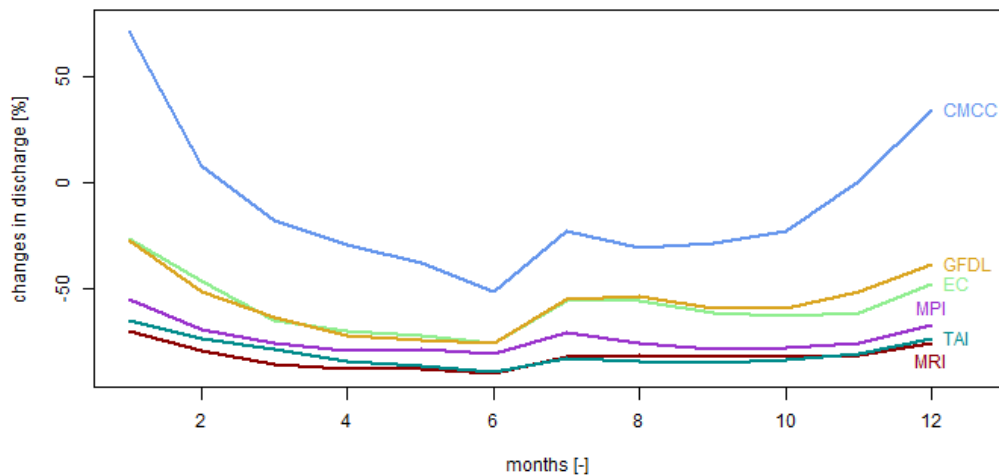


Fig. 6.24: Projections of seasonal runoff change estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the semi-distributed calibration variant in the period 1996-2005 and a 10 year historical period for reference.

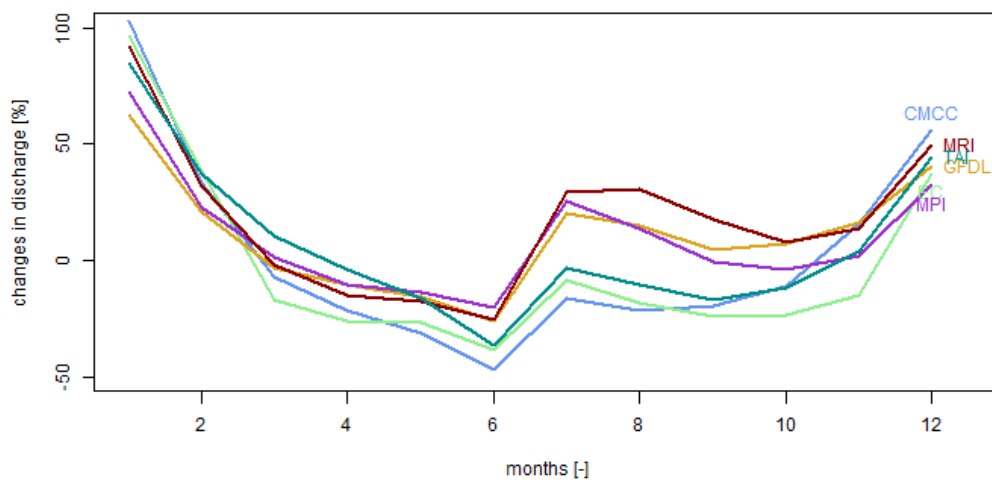


Fig. 6.25: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the snow calibration variant in the period 1996-2005 and a 10 year historical period for reference.

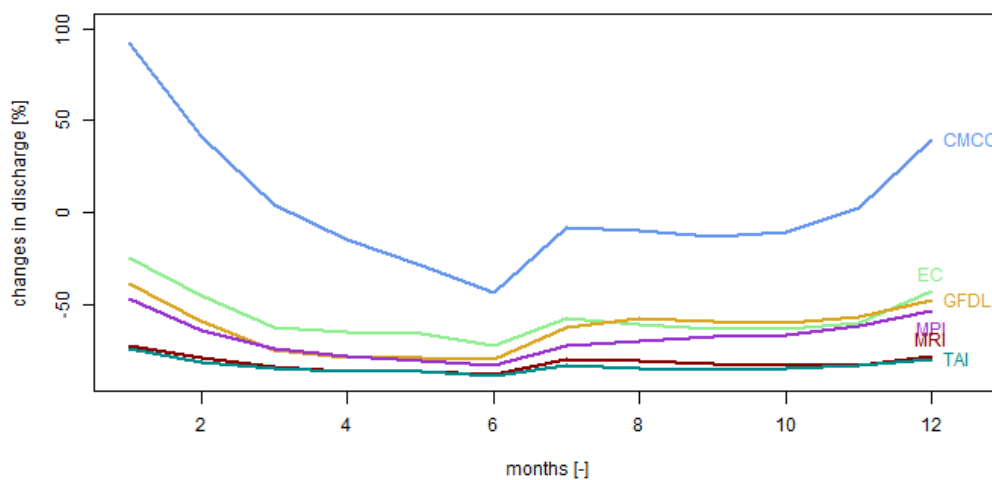


Fig. 6.26: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the snow calibration variant in the period 1996-2005 and a 10 year historical period for reference.

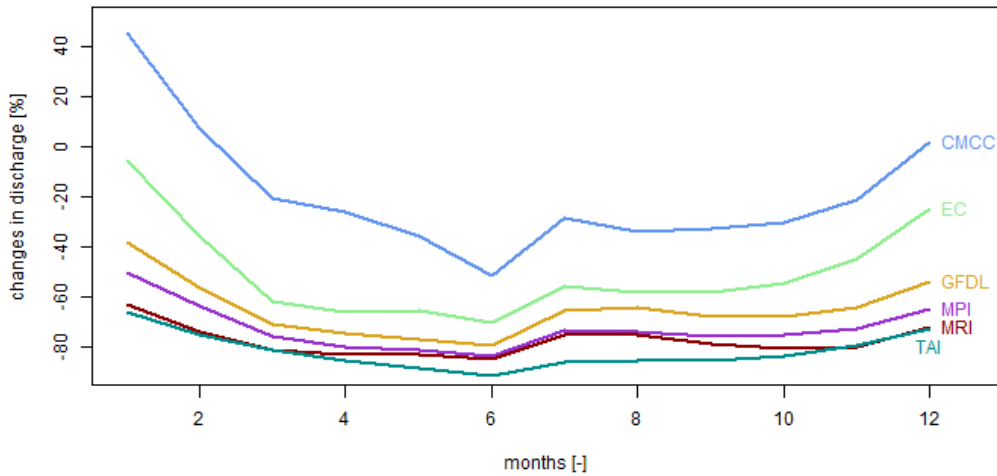


Fig. 6.27: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the snow calibration variant in the period 1996-2005 and a 10 year historical period for reference.

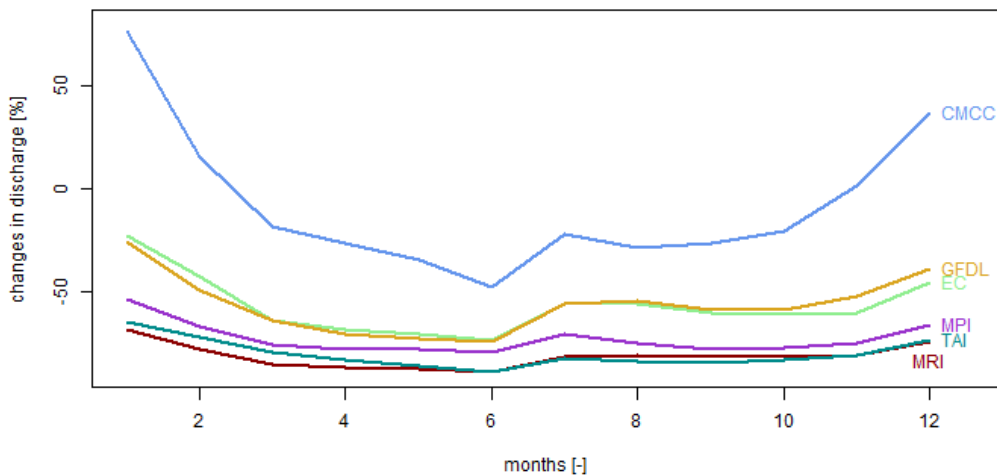


Fig. 6.28: Projections of seasonal runoff change estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the snow calibration variant in the period 1996-2005 and a 10 year historical period for reference.

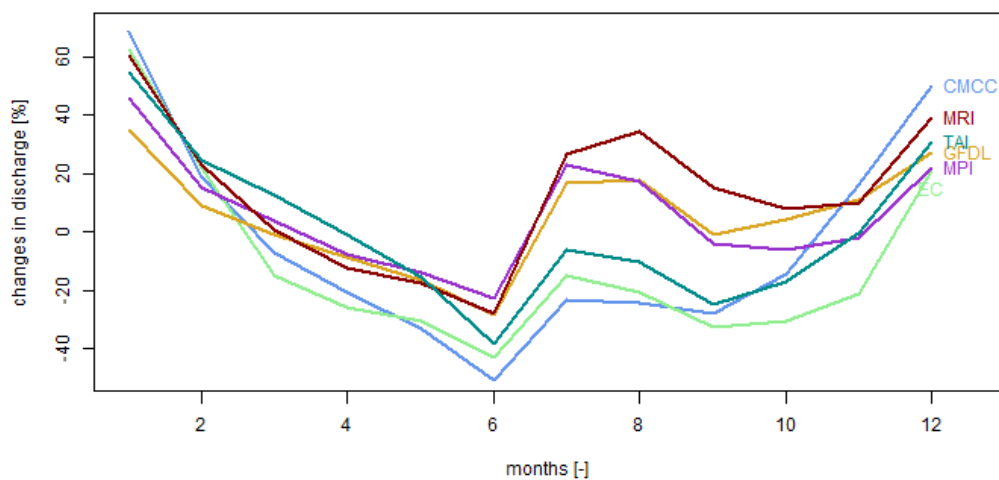


Fig. 6.29: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1996-2005 and a 10 year historical period for reference.

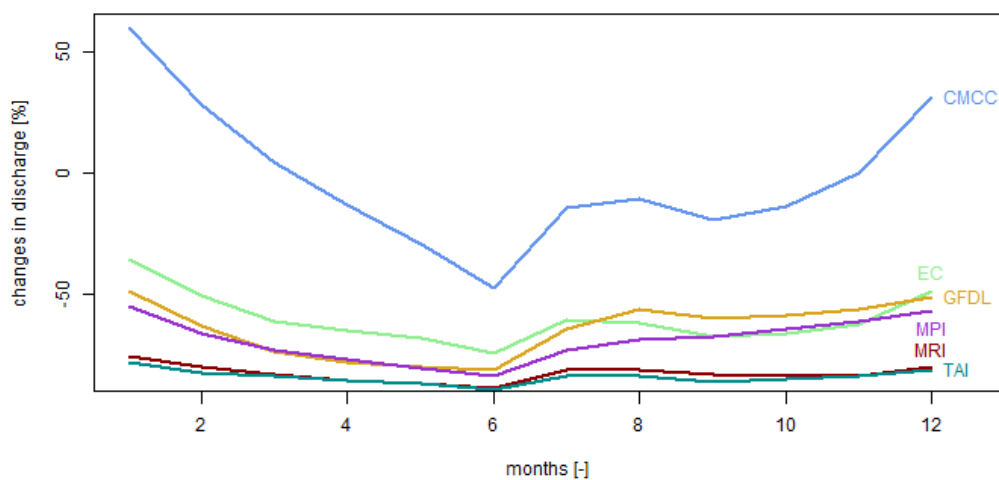


Fig. 6.30: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1996-2005 and a 10 year historical period for reference.

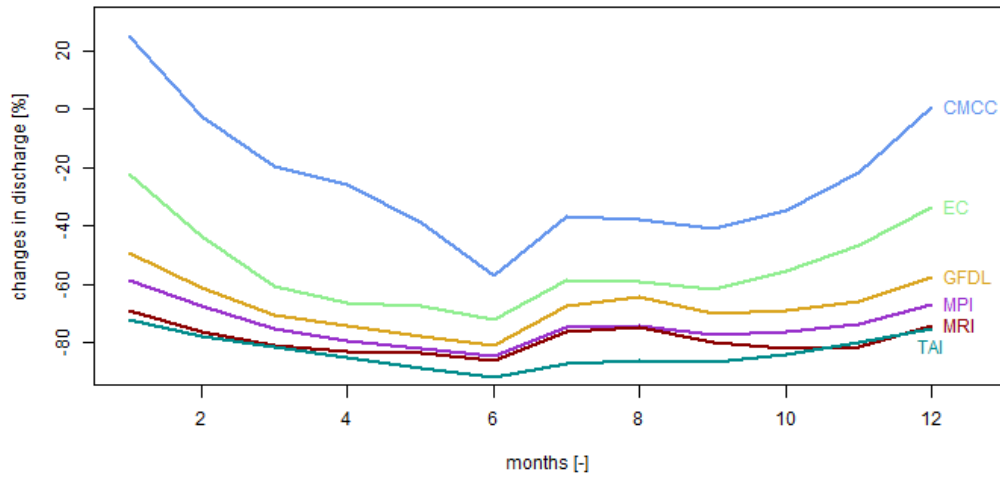


Fig. 6.31: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1996-2005 and a 10 year historical period for reference.

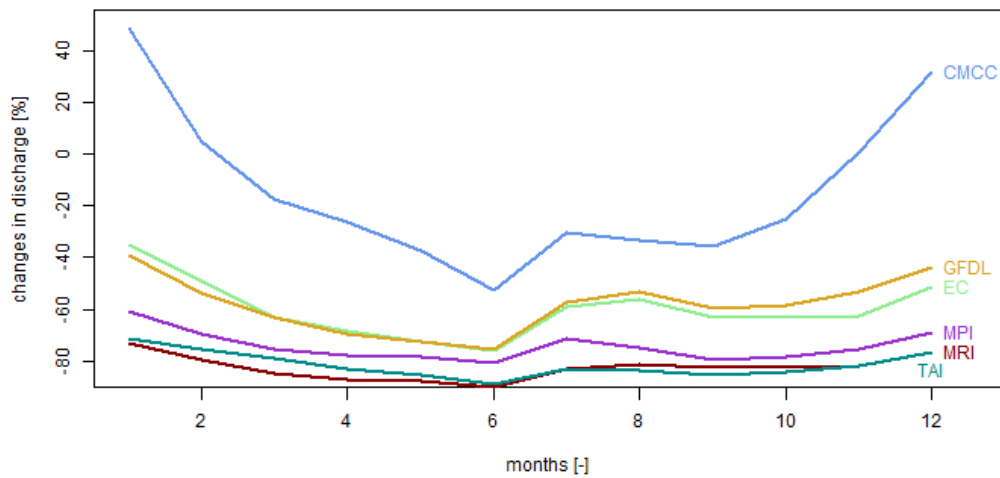


Fig. 6.32: Projections of seasonal runoff change estimated from climate scenarios representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1996-2005 and a 10 year historical period for reference.

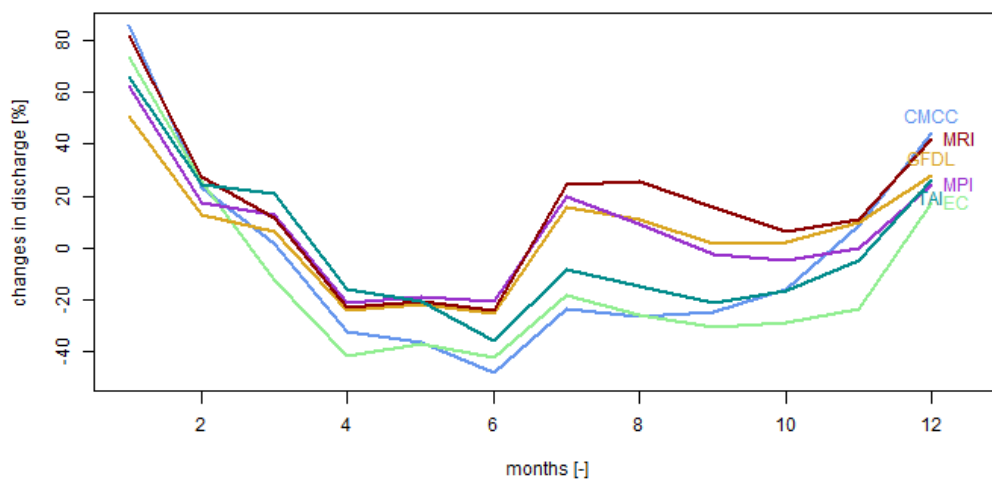


Fig. 6.33: Projections of seasonal runoff change estimated from climate scenarios representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1991-2000 and a 10 year historical period for reference.

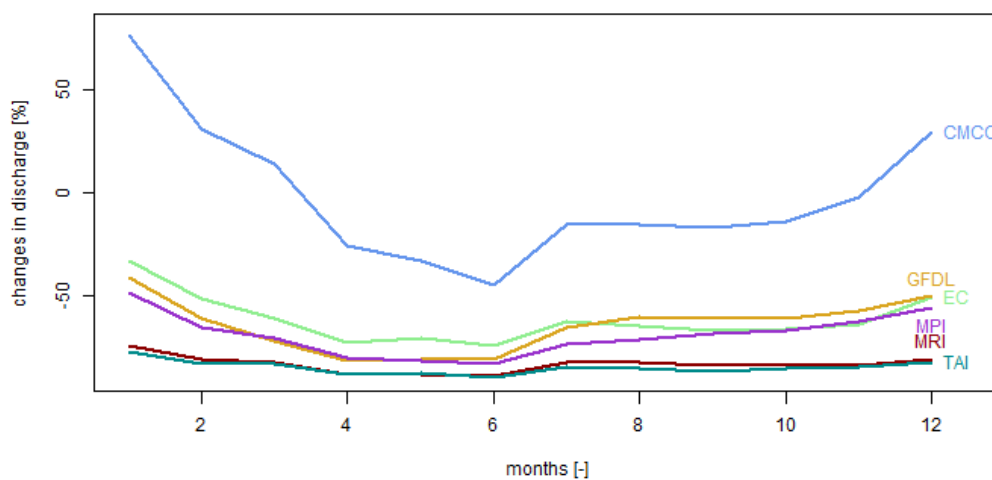


Fig. 6.34: Projections of seasonal runoff change estimated from climate scenarios representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1991-2000 and a 10 year historical period for reference.

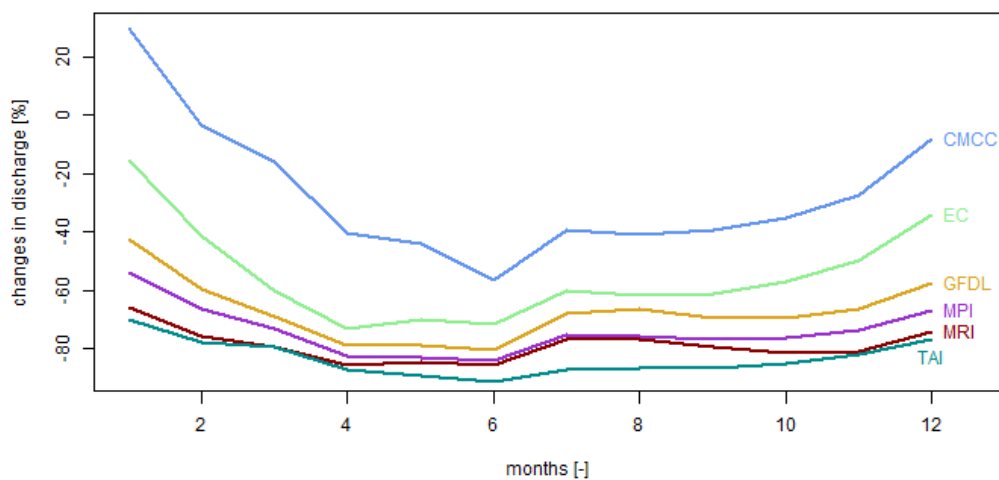


Fig. 6.35: Projections of seasonal runoff change estimated from climate scenarios representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the distributed calibration variant in the period 1991-2000 and a 10 year historical period for reference.

6.3.2 Comparison of annual data

Tab. 6.52: Changes in discharge for annual runoff for mean over 30 years (1/3) [%]

Variant	1	2	3	4	5	6	7	8	9	10
CMCC 1 lumped 86 126	47.84	-17.42	-10.27	-24.89	-43.57	-8.56	29.62	1.36	-26.82	-56.03
CMCC 1 lumped 91 126	53.30	-18.97	-8.18	-21.03	-44.52	-6.90	31.68	5.57	-25.07	-52.56
CMCC 1 lumped 96 126	39.06	-19.52	-5.78	-19.73	-41.36	-8.65	28.38	10.74	-22.28	-49.09
CMCC 2 semi 86 126	47.49	-18.33	-8.64	-26.63	-44.24	-5.16	31.21	0.19	-32.69	-59.41
CMCC 2 semi 91 126	46.45	-18.56	-4.59	-24.94	-44.24	-5.23	31.57	5.29	-29.62	-54.93
CMCC 2 semi 96 126	39.20	-20.83	-4.02	-22.10	-41.10	-6.01	30.96	11.10	-28.26	-52.85
CMCC 3 snow 96 126	38.96	-19.95	-6.21	-19.76	-39.85	-8.13	27.80	11.35	-23.41	-49.96
CMCC 3 snow 01 126	45.80	-21.13	-6.40	-25.24	-40.34	-10.04	27.94	11.72	-27.18	-53.18
CMCC 4 distributed 86 126	47.63	-15.12	-7.99	-22.56	-46.30	0.50	27.85	-1.24	-31.34	-63.84
CMCC 4 distributed 91 126	44.19	-16.32	-3.08	-27.54	-47.59	-3.45	26.80	2.86	-27.46	-58.86
CMCC 4 distributed 96 126	39.46	-21.93	0.63	-24.59	-44.55	-9.73	25.66	9.27	-25.36	-52.60
EC 1 lumped 86 126	56.02	-31.17	9.86	-27.17	-45.76	-10.34	27.17	-7.75	-31.26	-59.11
EC 1 lumped 91 126	62.65	-32.09	-7.06	-22.40	-46.23	-7.29	30.71	-3.00	-28.59	-56.06
EC 1 lumped 96 126	48.26	-31.12	-3.31	-20.09	-42.36	-6.07	28.62	4.26	-23.89	-52.50
EC 2 semi 86 126	53.12	-32.88	-8.90	-29.59	-46.96	-7.79	28.35	-10.34	-37.56	-63.11
EC 2 semi 91 126	52.36	-31.95	-3.76	-26.64	-46.09	-5.72	30.41	-3.99	-33.09	-58.73
EC 2 semi 96 126	44.21	-32.78	-2.30	-23.22	-42.69	-4.64	30.98	3.16	-30.07	-57.12
EC 3 snow 96 126	48.35	-31.10	-3.34	-19.59	-40.71	-5.46	28.65	6.08	-24.77	-53.02
EC 3 snow 01 126	51.46	-32.54	-5.03	-26.60	-42.58	-9.54	27.87	3.55	-29.01	-57.03
EC 4 distributed 86 126	49.33	-30.94	-10.42	-28.62	-49.79	-5.97	22.74	-13.59	-40.83	-68.38
EC 4 distributed 91 126	46.35	-32.02	-3.47	-30.52	-48.88	-7.89	23.52	-7.63	-34.05	-63.23
EC 4 distributed 96 126	38.95	-32.53	2.53	-26.21	-45.28	-9.32	25.97	2.14	-28.60	-57.37
GFDL 1 lumped 86 126	75.46	-19.05	-2.42	-14.40	-31.76	0.95	44.27	11.48	-16.27	-48.99
GFDL 1 lumped 91 126	77.49	-21.15	-1.10	-12.04	-32.79	2.66	46.60	14.49	-14.74	-46.49
GFDL 1 lumped 96 126	58.15	-22.33	-0.17	-12.29	-30.22	0.49	41.55	18.50	-11.91	-44.34
GFDL 2 semi 86 126	78.86	-20.44	0.00	-15.48	-32.01	5.12	46.68	10.81	-22.01	-52.45
GFDL 2 semi 91 126	75.28	-20.60	4.04	-14.36	-31.38	6.09	47.47	15.82	-18.39	-47.89
GFDL 2 semi 96 126	59.43	-24.18	1.73	-14.48	-29.75	3.09	44.58	18.90	-17.75	-48.56
GFDL 3 snow 96 126	58.54	-22.80	-0.70	-12.05	-28.33	0.76	41.05	19.53	-13.47	-45.41
GFDL 3 snow 01 126	70.36	-23.64	0.51	-16.03	-28.20	-1.09	42.60	20.33	-16.01	-47.49
GFDL 4 distributed 86 126	65.89	-19.76	-2.60	-14.56	-35.74	8.04	40.08	7.63	-25.93	-60.48
GFDL 4 distributed 91 126	62.11	-20.31	4.17	-19.56	-35.95	6.68	40.76	13.59	-18.91	-54.58
GFDL 4 distributed 96 126	50.98	-24.95	7.19	-17.26	-33.51	0.20	41.09	18.34	-16.41	-50.54
MPI 1 lumped 86 126	72.92	-17.37	2.22	-8.54	-30.89	4.38	50.57	12.82	-13.04	-48.82
MPI 1 lumped 91 126	75.48	-19.64	3.74	-6.02	-31.97	6.50	52.92	15.08	-11.46	-46.26

Continued on next page

Tab. 6.52: Changes in discharge for annual runoff for mean over 30 years (1/3) (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10
MPI 1 lumped 96 126	56.28	-20.91	4.56	-6.97	-29.59	4.14	47.05	18.54	-8.35	-44.56
MPI 2 semi 86 126	72.70	-18.54	4.75	-9.14	-31.03	8.83	53.37	12.18	-18.81	-52.28
MPI 2 semi 91 126	67.62	-18.70	8.80	-8.47	-30.48	9.90	53.56	16.33	-15.28	-48.06
MPI 2 semi 96 126	54.11	-22.35	6.49	-8.93	-29.08	7.09	50.19	18.94	-14.29	-48.97
MPI 3 snow 96 126	55.99	-21.33	3.89	-6.99	-27.85	4.27	46.22	19.33	-9.91	-45.72
MPI 3 snow 01 126	63.75	-21.93	4.77	-11.39	-27.87	2.28	47.65	19.78	-12.45	-47.96
MPI 4 distributed 86 126	68.34	-18.11	3.18	-6.32	-33.90	12.97	48.39	10.22	-22.19	-59.31
MPI 4 distributed 91 126	62.77	-18.71	10.36	-12.36	-34.14	11.40	48.78	16.58	-15.16	-53.81
MPI 4 distributed 96 126	50.18	-22.73	13.36	-11.39	-32.02	5.19	48.39	20.33	-11.57	-49.87
MRI 1 lumped 86 126	87.56	-10.67	5.29	-2.96	-26.40	9.17	52.72	18.71	-9.84	-46.47
MRI 1 lumped 91 126	88.29	-13.55	6.20	-1.04	-27.83	10.90	53.99	20.76	-8.61	-43.94
MRI 1 lumped 96 126	64.07	-15.39	5.76	-3.03	-25.56	7.59	47.27	23.48	-6.68	-42.84
MRI 2 semi 86 126	89.51	-11.71	7.70	-3.52	-26.46	13.89	55.30	18.13	-15.69	-49.97
MRI 2 semi 91 126	83.42	-12.42	11.37	-3.26	-25.98	14.66	54.90	22.31	-12.53	-45.57
MRI 2 semi 96 126	63.99	-16.97	7.37	-4.95	-24.85	10.76	50.26	23.78	-12.81	-47.24
MRI 3 snow 96 126	63.58	-15.88	4.74	-3.20	-23.84	7.77	46.40	24.09	-8.41	-44.17
MRI 3 snow 01 126	76.05	-16.64	5.69	-7.32	-23.70	5.83	47.78	24.81	-11.27	-46.16
MRI 4 distributed 86 126	79.10	-11.07	6.21	-1.15	-29.76	18.52	49.06	14.51	-18.64	-58.23
MRI 4 distributed 91 126	73.18	-11.37	13.26	-6.99	-29.90	16.86	49.40	21.27	-11.57	-52.13
MRI 4 distributed 96 126	58.12	-17.18	14.57	-7.54	-27.98	9.64	48.25	24.06	-9.88	-49.09
TAI 1 lumped 86 126	76.71	-18.99	2.44	-15.37	-36.68	-0.70	41.29	10.41	-22.62	-54.09
TAI 1 lumped 91 126	83.55	-19.92	5.55	-11.02	-36.92	2.67	44.48	14.68	-19.73	-50.58
TAI 1 lumped 96 126	65.93	-20.75	7.48	-9.90	-33.67	1.93	39.80	20.01	-16.14	-46.84
TAI 2 semi 86 126	77.01	-20.00	5.19	-16.80	-37.10	3.58	43.92	9.86	-28.33	-57.77
TAI 2 semi 91 126	74.76	-19.41	10.27	-14.81	-36.28	5.30	44.57	15.38	-24.19	-53.08
TAI 2 semi 96 126	64.87	-22.10	9.78	-12.15	-33.30	4.62	42.99	20.92	-21.88	-51.13
TAI 3 snow 96 126	66.34	-21.33	6.90	-9.89	-31.96	2.14	39.20	21.10	-17.69	-47.75
TAI 3 snow 01 126	73.96	-22.29	6.13	-16.24	-33.17	-1.05	39.17	20.25	-21.57	-51.39
TAI 4 distributed 86 126	72.62	-16.91	5.18	-11.84	-38.77	8.44	40.20	9.83	-29.24	-62.26
TAI 4 distributed 91 126	67.46	-17.76	12.20	-17.85	-39.05	5.35	40.04	14.45	-23.39	-57.55
TAI 4 distributed 96 126	56.79	-21.77	16.35	-15.08	-36.15	1.43	39.76	20.66	-19.40	-51.24
CMCC 1 lumped 86 245	57.77	-17.51	-2.20	-18.00	-39.31	-4.29	34.51	8.53	-23.91	-55.51
CMCC 1 lumped 91 245	63.55	-19.24	-0.18	-14.24	-40.27	-2.36	36.31	12.38	-21.94	-52.22
CMCC 1 lumped 96 245	48.12	-20.02	1.39	-13.58	-37.36	-4.33	31.66	17.07	-18.87	-49.37
CMCC 2 semi 86 245	56.81	-18.45	-0.09	-19.61	-39.81	-0.57	36.06	7.67	-29.83	-59.03
CMCC 2 semi 91 245	54.56	-18.64	3.96	-18.27	-39.73	-0.32	35.80	12.65	-26.61	-54.75

Continued on next page

Tab. 6.52: Changes in discharge for annual runoff for mean over 30 years (1/3) (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10
CMCC 2 semi 96 245	47.12	-21.31	3.31	-15.91	-37.16	-1.82	33.98	17.48	-24.91	-53.54
CMCC 3 snow 96 245	47.53	-20.41	0.72	-13.76	-35.92	-4.23	31.01	17.76	-20.32	-50.41
CMCC 3 snow 01 245	54.26	-21.32	0.80	-19.16	-36.30	-6.12	31.61	17.94	-23.70	-53.35
CMCC 4 distributed 86 245	58.35	-16.02	0.28	-14.72	-41.76	4.44	32.45	6.74	-29.90	-63.96
CMCC 4 distributed 91 245	53.77	-17.03	5.90	-20.71	-42.79	1.32	31.49	11.27	-25.03	-59.16
CMCC 4 distributed 96 245	45.96	-22.08	8.93	-18.27	-40.19	-4.89	29.99	16.82	-22.29	-53.55
EC 1 lumped 86 245	-36.69	-69.21	-62.02	-69.46	-76.62	-61.27	-44.43	-60.08	-70.26	-82.76
EC 1 lumped 91 245	-33.75	-69.70	-60.93	-67.47	-76.86	-60.02	-43.03	-58.22	-69.19	-81.44
EC 1 lumped 96 245	-37.93	-68.91	-58.98	-66.22	-75.01	-59.23	-43.65	-54.85	-67.06	-79.93
EC 2 semi 86 245	-38.69	-70.14	-61.81	-70.77	-77.23	-60.28	-44.12	-61.32	-73.32	-84.65
EC 2 semi 91 245	-38.77	-69.73	-59.75	-69.53	-76.87	-59.42	-43.41	-58.76	-71.42	-82.73
EC 2 semi 96 245	-40.21	-69.64	-58.60	-67.78	-75.19	-58.72	-42.74	-55.35	-69.99	-82.10
EC 3 snow 96 245	-37.87	-68.85	-58.93	-65.97	-74.27	-58.92	-43.53	-54.03	-67.50	-80.21
EC 3 snow 01 245	-37.53	-69.47	-59.46	-69.05	-75.05	-60.64	-43.71	-54.89	-69.33	-82.02
EC 4 distributed 86 245	-36.47	-69.34	-62.43	-69.80	-78.64	-59.58	-46.09	-62.13	-74.67	-86.79
EC 4 distributed 91 245	-37.86	-69.80	-59.43	-71.07	-78.06	-60.47	-45.88	-59.90	-71.72	-84.60
EC 4 distributed 96 245	-38.76	-69.92	-56.49	-68.55	-76.26	-60.65	-44.89	-55.49	-69.55	-81.94
GFDL 1 lumped 86 245	-39.15	-74.53	-72.27	-74.83	-78.95	-68.73	-56.49	-66.43	-75.86	-84.96
GFDL 1 lumped 91 245	-39.14	-75.34	-72.09	-74.18	-79.41	-68.27	-56.23	-65.57	-75.56	-84.24
GFDL 1 lumped 96 245	-47.01	-75.38	-71.59	-73.93	-78.33	-68.77	-57.41	-64.17	-74.72	-83.52
GFDL 2 semi 86 245	-37.00	-74.93	-71.74	-75.31	-78.98	-67.38	-55.91	-66.77	-77.78	-85.98
GFDL 2 semi 91 245	-38.30	-74.97	-70.57	-74.81	-78.77	-66.98	-55.67	-65.00	-76.69	-84.53
GFDL 2 semi 96 245	-45.88	-75.90	-71.08	-74.65	-78.06	-67.80	-56.44	-64.02	-76.64	-84.69
GFDL 3 snow 96 245	-47.04	-75.49	-71.70	-73.78	-77.73	-68.64	-57.46	-63.72	-75.15	-83.79
GFDL 3 snow 01 245	-41.80	-75.85	-71.29	-74.92	-77.55	-69.09	-56.80	-63.41	-75.97	-84.39
GFDL 4 distributed 86 245	-42.70	-74.46	-72.47	-75.31	-80.32	-66.30	-58.24	-68.32	-78.90	-88.41
GFDL 4 distributed 91 245	-43.27	-74.43	-70.30	-75.91	-80.19	-66.36	-57.71	-66.02	-76.75	-86.27
GFDL 4 distributed 96 245	-48.46	-75.90	-69.51	-74.92	-79.17	-68.58	-57.55	-64.25	-76.22	-85.12
MPI 1 lumped 86 245	-43.23	-78.37	-73.51	-75.22	-81.59	-72.73	-61.81	-69.13	-78.30	-85.71
MPI 1 lumped 91 245	-42.91	-78.85	-73.11	-74.54	-81.83	-72.12	-61.39	-68.33	-77.80	-84.95
MPI 1 lumped 96 245	-50.96	-79.27	-73.02	-74.57	-81.17	-72.78	-62.88	-67.49	-77.14	-84.15
MPI 2 semi 86 245	-40.86	-78.50	-72.67	-75.27	-81.50	-71.43	-61.06	-69.02	-79.67	-86.49
MPI 2 semi 91 245	-42.28	-78.53	-71.57	-74.98	-81.34	-71.06	-61.05	-67.68	-78.74	-85.19
MPI 2 semi 96 245	-49.69	-79.62	-72.37	-74.82	-80.91	-71.81	-62.04	-67.04	-78.61	-85.05
MPI 3 snow 96 245	-51.11	-79.44	-73.24	-74.51	-80.73	-72.74	-63.09	-67.21	-77.54	-84.43
MPI 3 snow 01 245	-46.12	-79.72	-72.99	-75.46	-80.66	-73.19	-62.68	-66.94	-78.32	-84.91

Continued on next page

Tab. 6.52: Changes in discharge for annual runoff for mean over 30 years (1/3) (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10
MPI 4 distributed 86 245	-46.65	-77.81	-72.94	-74.47	-82.17	-70.13	-62.72	-69.74	-80.24	-88.36
MPI 4 distributed 91 245	-48.31	-77.74	-71.10	-75.89	-82.29	-70.18	-62.44	-67.83	-78.63	-86.71
MPI 4 distributed 96 245	-54.18	-79.17	-70.66	-75.49	-81.75	-72.16	-62.58	-66.84	-77.83	-85.50
MRI 1 lumped 86 245	-73.26	-86.31	-84.03	-86.28	-89.26	-83.41	-76.19	-82.07	-86.56	-92.36
MRI 1 lumped 91 245	-72.66	-86.70	-83.83	-85.83	-89.49	-83.19	-75.99	-81.69	-86.35	-91.93
MRI 1 lumped 96 245	-74.77	-86.67	-83.49	-85.72	-88.96	-83.34	-76.74	-80.86	-85.75	-91.66
MRI 2 semi 86 245	-73.79	-86.65	-83.86	-86.72	-89.45	-82.93	-76.02	-82.45	-87.77	-93.07
MRI 2 semi 91 245	-74.35	-86.65	-83.25	-86.54	-89.40	-82.82	-76.08	-81.73	-87.20	-92.36
MRI 2 semi 96 245	-75.51	-86.95	-83.34	-86.32	-89.02	-83.07	-76.41	-81.04	-86.94	-92.52
MRI 3 snow 96 245	-74.81	-86.71	-83.56	-85.71	-88.67	-83.29	-76.79	-80.68	-86.04	-91.84
MRI 3 snow 01 245	-74.21	-86.87	-83.52	-86.72	-88.77	-83.69	-76.58	-80.71	-86.60	-92.34
MRI 4 distributed 86 245	-73.31	-86.45	-84.13	-86.29	-90.14	-82.52	-76.88	-82.85	-88.46	-94.24
MRI 4 distributed 91 245	-74.08	-86.63	-83.05	-87.09	-90.05	-82.94	-77.02	-82.00	-87.15	-93.28
MRI 4 distributed 96 245	-74.86	-87.20	-82.46	-86.54	-89.57	-83.71	-77.18	-81.09	-86.79	-92.63
TAI 1 lumped 86 245	-74.82	-87.80	-85.41	-87.45	-90.31	-85.22	-78.54	-83.95	-88.32	-93.18
TAI 1 lumped 91 245	-73.91	-88.04	-85.10	-86.93	-90.42	-84.88	-78.18	-83.51	-88.03	-92.73
TAI 1 lumped 96 245	-76.01	-88.10	-84.76	-86.71	-89.92	-84.98	-78.82	-82.73	-87.46	-92.29
TAI 2 semi 86 245	-74.89	-88.04	-85.17	-87.77	-90.38	-84.66	-78.28	-84.17	-89.32	-93.79
TAI 2 semi 91 245	-75.16	-88.01	-84.54	-87.54	-90.29	-84.51	-78.27	-83.52	-88.79	-93.13
TAI 2 semi 96 245	-76.33	-88.36	-84.57	-87.17	-89.88	-84.66	-78.47	-82.79	-88.45	-93.02
TAI 3 snow 96 245	-75.92	-88.17	-84.81	-86.67	-89.64	-84.93	-78.87	-82.56	-87.68	-92.43
TAI 3 snow 01 245	-75.03	-88.32	-84.83	-87.61	-89.76	-85.35	-78.77	-82.62	-88.20	-92.97
TAI 4 distributed 86 245	-75.03	-87.76	-85.41	-87.31	-90.80	-84.14	-78.92	-84.31	-89.75	-94.65
TAI 4 distributed 91 245	-75.76	-87.91	-84.36	-88.10	-90.81	-84.57	-79.00	-83.52	-88.70	-93.86
TAI 4 distributed 96 245	-76.64	-88.46	-83.73	-87.49	-90.36	-85.17	-79.02	-82.73	-88.23	-93.03
CMCC 1 lumped 86 370	4.44	-34.36	-25.35	-43.22	-56.90	-27.30	4.45	-19.21	-40.65	-68.21
CMCC 1 lumped 91 370	12.53	-35.42	-22.93	-39.12	-57.36	-25.54	7.13	-15.40	-38.64	-65.29
CMCC 1 lumped 96 370	8.77	-34.03	-19.05	-36.19	-53.76	-25.07	6.33	-8.77	-34.55	-62.17
CMCC 2 semi 86 370	0.64	-35.84	-24.77	-45.52	-58.09	-25.12	5.13	-21.19	-46.37	-71.52
CMCC 2 semi 91 370	2.54	-35.49	-20.89	-43.34	-57.78	-24.73	6.16	-16.51	-43.34	-67.93
CMCC 2 semi 96 370	5.96	-35.09	-17.92	-38.85	-54.11	-23.65	8.43	-8.97	-39.93	-65.83
CMCC 3 snow 96 370	8.59	-34.06	-19.08	-35.90	-52.56	-24.75	6.31	-7.65	-35.59	-62.85
CMCC 3 snow 01 370	7.05	-35.04	-20.10	-41.81	-53.67	-27.27	5.88	-8.73	-39.04	-66.15
CMCC 4 distributed 86 370	12.47	-33.31	-24.01	-41.10	-59.16	-21.82	4.16	-20.46	-46.23	-74.25
CMCC 4 distributed 91 370	9.91	-34.88	-19.63	-45.13	-59.43	-25.57	2.51	-17.87	-42.13	-70.50
CMCC 4 distributed 96 370	14.43	-37.02	-13.82	-39.14	-55.78	-27.35	3.67	-9.23	-38.44	-64.49

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Tab. 6.52: Changes in discharge for annual runoff for mean over 30 years (1/3) (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10
EC 1 lumped 86 370	-14.98	-66.96	-59.15	-66.12	-73.90	-57.57	-39.73	-55.49	-67.39	-79.74
EC 1 lumped 91 370	-12.39	-67.42	-58.04	-64.15	-74.21	-56.31	-38.18	-53.38	-66.25	-78.34
EC 1 lumped 96 370	-20.96	-67.01	-56.15	-62.72	-72.23	-55.50	-38.85	-49.83	-64.22	-76.47
EC 2 semi 86 370	-14.33	-67.62	-58.64	-67.22	-74.28	-56.21	-39.08	-56.48	-70.30	-81.55
EC 2 semi 91 370	-14.43	-67.19	-56.23	-65.78	-73.78	-55.11	-37.91	-53.22	-68.12	-79.31
EC 2 semi 96 370	-21.28	-67.71	-55.46	-64.00	-72.08	-54.51	-37.43	-49.86	-66.99	-78.45
EC 3 snow 96 370	-20.84	-67.08	-56.11	-62.39	-71.39	-55.16	-38.72	-48.80	-64.63	-76.68
EC 3 snow 01 370	-16.56	-67.74	-56.58	-65.54	-71.98	-56.82	-38.85	-49.66	-66.44	-78.44
EC 4 distributed 86 370	-19.25	-66.29	-59.51	-66.96	-75.72	-55.28	-41.96	-58.37	-71.85	-83.98
EC 4 distributed 91 370	-20.28	-66.77	-56.02	-67.31	-75.05	-55.93	-41.15	-55.30	-68.53	-81.29
EC 4 distributed 96 370	-25.92	-67.32	-53.30	-64.96	-73.25	-56.56	-39.79	-50.48	-66.21	-78.62
GFDL 1 lumped 86 370	-48.30	-74.64	-70.24	-75.69	-79.53	-68.33	-55.75	-66.18	-75.67	-85.77
GFDL 1 lumped 91 370	-46.86	-75.34	-69.73	-74.61	-79.86	-67.75	-55.07	-64.99	-75.15	-84.91
GFDL 1 lumped 96 370	-52.09	-75.34	-69.05	-74.27	-78.87	-68.28	-56.40	-63.40	-74.28	-84.08
GFDL 2 semi 86 370	-48.02	-75.18	-69.70	-76.39	-79.75	-67.10	-55.28	-66.66	-77.67	-86.91
GFDL 2 semi 91 370	-48.53	-75.15	-68.30	-75.75	-79.60	-66.82	-54.98	-64.82	-76.48	-85.49
GFDL 2 semi 96 370	-52.10	-75.91	-68.54	-75.25	-78.85	-67.50	-55.62	-63.48	-76.28	-85.42
GFDL 3 snow 96 370	-52.01	-75.44	-69.17	-74.15	-78.31	-68.19	-56.52	-63.03	-74.74	-84.37
GFDL 3 snow 01 370	-49.40	-75.80	-69.06	-75.85	-78.43	-68.91	-56.30	-63.04	-75.76	-85.26
GFDL 4 distributed 86 370	-49.83	-74.68	-70.26	-76.16	-80.89	-65.94	-57.07	-67.82	-78.54	-89.04
GFDL 4 distributed 91 370	-50.66	-74.96	-68.13	-77.01	-80.93	-66.58	-56.95	-66.07	-76.54	-87.16
GFDL 4 distributed 96 370	-52.94	-76.30	-66.94	-75.88	-79.99	-68.59	-56.91	-63.88	-75.87	-85.72
MPI 1 lumped 86 370	-57.85	-79.72	-75.38	-79.25	-83.76	-74.80	-64.39	-72.34	-80.06	-88.48
MPI 1 lumped 91 370	-56.77	-80.24	-74.96	-78.41	-84.04	-74.28	-63.87	-71.44	-79.62	-87.78
MPI 1 lumped 96 370	-61.31	-80.48	-74.69	-78.34	-83.38	-74.78	-65.17	-70.43	-78.93	-87.23
MPI 2 semi 86 370	-57.79	-80.04	-74.86	-79.63	-83.88	-73.78	-63.87	-72.61	-81.56	-89.38
MPI 2 semi 91 370	-58.62	-80.07	-73.82	-79.24	-83.81	-73.55	-63.80	-71.30	-80.68	-88.31
MPI 2 semi 96 370	-61.50	-80.88	-74.28	-78.97	-83.34	-74.10	-64.51	-70.43	-80.48	-88.31
MPI 3 snow 96 370	-61.40	-80.59	-74.84	-78.32	-82.99	-74.74	-65.34	-70.21	-79.31	-87.47
MPI 3 snow 01 370	-59.35	-80.89	-74.82	-79.67	-83.11	-75.31	-65.23	-70.30	-80.17	-88.22
MPI 4 distributed 86 370	-58.54	-79.64	-75.12	-78.96	-84.62	-72.70	-65.07	-73.18	-82.04	-90.98
MPI 4 distributed 91 370	-59.67	-79.83	-73.44	-80.01	-84.70	-73.27	-65.11	-71.78	-80.48	-89.57
MPI 4 distributed 96 370	-62.40	-81.02	-72.74	-79.51	-84.13	-74.74	-65.29	-70.43	-79.92	-88.48
MRI 1 lumped 86 370	-66.02	-83.20	-79.86	-82.45	-86.19	-79.08	-70.58	-77.92	-82.85	-90.12
MRI 1 lumped 91 370	-65.64	-83.70	-79.58	-81.93	-86.44	-78.66	-70.20	-77.39	-82.56	-89.63
MRI 1 lumped 96 370	-69.40	-83.91	-79.40	-82.10	-85.87	-79.13	-71.35	-76.54	-81.96	-89.33

Continued on next page

Tab. 6.52: Changes in discharge for annual runoff for mean over 30 years (1/3) (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10
MRI 2 semi 86 370	-65.97	-83.45	-79.41	-82.62	-86.25	-78.22	-70.15	-78.18	-84.04	-90.84
MRI 2 semi 91 370	-66.98	-83.52	-78.61	-82.45	-86.15	-78.01	-70.12	-77.24	-83.33	-89.99
MRI 2 semi 96 370	-69.70	-84.19	-79.05	-82.52	-85.77	-78.56	-70.79	-76.59	-83.16	-90.22
MRI 3 snow 96 370	-69.43	-83.97	-79.52	-82.08	-85.50	-79.08	-71.46	-76.37	-82.29	-89.56
MRI 3 snow 01 370	-67.65	-84.08	-79.33	-82.93	-85.48	-79.47	-71.14	-76.28	-82.79	-89.97
MRI 4 distributed 86 370	-67.41	-83.36	-79.75	-82.28	-86.94	-77.46	-71.37	-78.80	-84.77	-92.39
MRI 4 distributed 91 370	-68.35	-83.50	-78.47	-83.38	-87.00	-77.80	-71.35	-77.63	-83.41	-91.26
MRI 4 distributed 96 370	-70.54	-84.37	-77.86	-83.05	-86.49	-79.11	-71.39	-76.69	-82.77	-90.55
TAI 1 lumped 86 370	-69.80	-86.43	-83.64	-86.43	-90.04	-84.17	-77.74	-81.26	-87.80	-92.80
TAI 1 lumped 91 370	-68.22	-86.60	-83.14	-85.71	-90.07	-83.66	-77.33	-80.46	-87.34	-92.17
TAI 1 lumped 96 370	-71.21	-86.76	-82.77	-85.30	-89.47	-83.76	-77.96	-79.52	-86.74	-91.39
TAI 2 semi 86 370	-69.12	-86.61	-83.26	-86.75	-90.09	-83.52	-77.44	-81.30	-88.77	-93.40
TAI 2 semi 91 370	-69.07	-86.58	-82.48	-86.41	-90.00	-83.33	-77.42	-80.36	-88.15	-92.59
TAI 2 semi 96 370	-70.72	-87.03	-82.44	-85.67	-89.36	-83.34	-77.53	-79.31	-87.70	-92.03
TAI 3 snow 96 370	-71.08	-86.88	-82.87	-85.28	-89.18	-83.74	-78.04	-79.33	-86.99	-91.53
TAI 3 snow 01 370	-69.09	-87.09	-83.01	-86.33	-89.33	-84.24	-78.11	-79.41	-87.63	-92.15
TAI 4 distributed 86 370	-70.70	-85.82	-83.14	-85.92	-90.30	-82.52	-78.00	-81.28	-88.67	-94.08
TAI 4 distributed 91 370	-71.65	-85.97	-82.23	-86.91	-90.51	-83.17	-78.23	-80.68	-87.92	-93.32
TAI 4 distributed 96 370	-72.95	-87.02	-81.60	-86.21	-89.95	-84.08	-78.39	-79.70	-87.33	-92.14
CMCC 1 lumped 86 585	36.90	-25.22	-20.66	-34.47	-50.89	-18.57	15.90	-9.94	-34.41	-63.50
CMCC 1 lumped 91 585	43.37	-26.54	-18.39	-30.73	-51.59	-16.64	18.14	-6.42	-32.57	-60.32
CMCC 1 lumped 96 585	31.19	-26.55	-15.26	-28.88	-48.27	-16.95	15.82	-0.66	-29.55	-57.15
CMCC 2 semi 86 585	36.02	-26.39	-19.78	-36.69	-52.01	-15.98	16.62	-11.92	-40.30	-66.95
CMCC 2 semi 91 585	35.88	-26.38	-16.00	-35.06	-51.87	-15.61	16.97	-7.57	-37.41	-63.07
CMCC 2 semi 96 585	30.86	-28.09	-14.09	-31.59	-48.55	-15.22	17.74	-1.17	-35.35	-61.12
CMCC 3 snow 96 585	31.33	-27.01	-15.45	-28.81	-46.95	-16.69	15.62	0.18	-30.75	-57.95
CMCC 3 snow 01 585	36.40	-28.43	-16.23	-34.59	-47.88	-19.05	15.34	-0.64	-34.18	-61.50
CMCC 4 distributed 86 585	37.51	-23.21	-19.01	-32.48	-53.40	-11.36	14.70	-11.97	-40.20	-70.34
CMCC 4 distributed 91 585	34.96	-24.79	-14.37	-36.97	-54.07	-15.57	13.38	-8.80	-35.93	-66.15
CMCC 4 distributed 96 585	32.01	-29.18	-9.50	-32.75	-50.95	-18.92	13.37	-1.73	-33.02	-60.01
EC 1 lumped 86 585	-35.75	-70.33	-63.76	-71.12	-76.77	-62.44	-45.05	-60.70	-71.10	-83.21
EC 1 lumped 91 585	-32.45	-70.92	-62.76	-69.28	-77.03	-61.38	-43.69	-58.88	-70.18	-81.95
EC 1 lumped 96 585	-36.56	-69.95	-60.63	-67.68	-75.04	-60.34	-43.92	-55.42	-68.04	-80.53
EC 2 semi 86 585	-37.17	-71.20	-63.55	-72.47	-77.29	-61.35	-44.71	-61.90	-74.14	-84.89
EC 2 semi 91 585	-36.63	-70.84	-61.46	-71.13	-76.83	-60.46	-43.73	-59.09	-72.29	-82.98
EC 2 semi 96 585	-38.57	-70.58	-60.18	-69.26	-75.09	-59.65	-42.83	-55.79	-70.92	-82.47

Continued on next page

Tab. 6.52: Changes in discharge for annual runoff for mean over 30 years (1/3) (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10
EC 3 snow 96 585	-36.25	-69.90	-60.46	-67.25	-74.19	-59.98	-43.70	-54.39	-68.39	-80.73
EC 3 snow 01 585	-35.72	-70.37	-60.83	-70.32	-74.77	-61.51	-43.63	-55.14	-70.01	-82.31
EC 4 distributed 86 585	-35.80	-70.55	-64.40	-72.39	-78.98	-60.86	-47.35	-63.57	-76.06	-87.04
EC 4 distributed 91 585	-36.90	-70.72	-61.28	-72.62	-78.28	-61.32	-46.80	-60.74	-72.63	-84.64
EC 4 distributed 96 585	-37.37	-70.67	-58.15	-69.54	-76.20	-61.56	-45.22	-55.84	-70.58	-82.10
GFDL 1 lumped 86 585	-29.44	-68.07	-62.91	-65.42	-73.22	-60.64	-44.68	-56.96	-68.80	-81.00
GFDL 1 lumped 91 585	-29.02	-68.95	-62.48	-64.63	-73.58	-59.98	-44.12	-55.90	-68.27	-79.98
GFDL 1 lumped 96 585	-38.90	-69.67	-62.51	-65.22	-72.75	-61.29	-46.45	-54.89	-67.48	-79.19
GFDL 2 semi 86 585	-27.42	-68.27	-61.79	-65.48	-73.10	-58.79	-43.69	-56.85	-70.70	-82.09
GFDL 2 semi 91 585	-29.24	-68.58	-60.47	-65.36	-72.96	-58.64	-43.84	-55.27	-69.57	-80.43
GFDL 2 semi 96 585	-37.77	-70.24	-61.69	-65.79	-72.41	-59.99	-45.41	-54.52	-69.53	-80.57
GFDL 3 snow 96 585	-39.00	-69.85	-62.87	-65.23	-72.09	-61.20	-46.86	-54.66	-68.02	-79.56
GFDL 3 snow 01 585	-32.97	-70.05	-62.22	-66.32	-71.88	-61.62	-46.13	-54.07	-68.83	-80.17
GFDL 4 distributed 86 585	-34.08	-67.87	-62.15	-64.83	-74.19	-56.68	-46.01	-58.07	-71.25	-85.00
GFDL 4 distributed 91 585	-36.04	-67.92	-59.81	-67.21	-74.49	-56.86	-45.85	-55.45	-69.22	-82.90
GFDL 4 distributed 96 585	-42.15	-70.29	-59.17	-67.09	-73.84	-60.14	-46.15	-54.29	-68.41	-81.40
MPI 1 lumped 86 585	-59.84	-79.63	-74.86	-78.17	-83.66	-74.32	-63.19	-73.60	-79.20	-87.66
MPI 1 lumped 91 585	-58.65	-80.13	-74.34	-77.25	-83.86	-73.72	-62.36	-72.77	-78.71	-86.94
MPI 1 lumped 96 585	-62.63	-80.35	-73.91	-77.30	-83.17	-74.15	-63.60	-71.59	-77.87	-86.31
MPI 2 semi 86 585	-60.06	-79.90	-74.24	-78.34	-83.73	-73.22	-62.48	-73.82	-80.61	-88.55
MPI 2 semi 91 585	-60.84	-79.91	-73.11	-77.96	-83.58	-72.95	-62.26	-72.58	-79.67	-87.46
MPI 2 semi 96 585	-63.14	-80.68	-73.38	-77.79	-83.09	-73.41	-62.79	-71.47	-79.27	-87.42
MPI 3 snow 96 585	-62.68	-80.46	-74.04	-77.28	-82.77	-74.09	-63.79	-71.35	-78.24	-86.58
MPI 3 snow 01 585	-61.19	-80.66	-73.95	-78.57	-82.89	-74.66	-63.59	-71.40	-78.93	-87.31
MPI 4 distributed 86 585	-60.16	-79.59	-74.45	-77.52	-84.35	-72.13	-63.51	-74.06	-81.15	-90.13
MPI 4 distributed 91 585	-61.34	-79.78	-72.71	-78.94	-84.42	-72.69	-63.42	-72.67	-79.54	-88.81
MPI 4 distributed 96 585	-63.56	-80.78	-71.66	-78.44	-83.78	-73.97	-63.27	-71.18	-78.54	-87.56
MRI 1 lumped 86 585	-70.35	-86.32	-84.32	-86.87	-89.48	-83.59	-76.67	-82.56	-87.02	-92.55
MRI 1 lumped 91 585	-69.71	-86.62	-84.08	-86.35	-89.69	-83.27	-76.44	-82.12	-86.77	-92.08
MRI 1 lumped 96 585	-72.46	-86.58	-83.65	-86.05	-89.02	-83.26	-77.00	-81.15	-86.16	-91.66
MRI 2 semi 86 585	-70.10	-86.60	-84.14	-87.30	-89.63	-83.06	-76.48	-82.96	-88.22	-93.19
MRI 2 semi 91 585	-70.54	-86.53	-83.45	-87.00	-89.52	-82.80	-76.41	-82.10	-87.59	-92.43
MRI 2 semi 96 585	-72.62	-86.85	-83.45	-86.60	-88.97	-82.90	-76.59	-81.25	-87.30	-92.41
MRI 3 snow 96 585	-72.36	-86.66	-83.70	-86.00	-88.70	-83.19	-77.02	-80.88	-86.40	-91.80
MRI 3 snow 01 585	-70.99	-86.86	-83.68	-87.02	-88.79	-83.63	-76.82	-80.93	-86.96	-92.31
MRI 4 distributed 86 585	-71.07	-86.21	-84.36	-86.81	-90.28	-82.60	-77.38	-83.42	-88.80	-94.21

Continued on next page

Tab. 6.52: Changes in discharge for annual runoff for mean over 30 years (1/3) (Continuation)

Variant	1	2	3	4	5	6	7	8	9	10
MRI 4 distributed 91 585	-71.73	-86.35	-83.23	-87.43	-90.13	-82.91	-77.34	-82.44	-87.55	-93.21
MRI 4 distributed 96 585	-72.99	-86.93	-82.52	-86.61	-89.48	-83.49	-77.29	-81.32	-87.02	-92.40
TAI 1 lumped 86 585	-67.30	-85.14	-80.75	-84.14	-88.14	-81.79	-74.16	-79.50	-85.66	-91.71
TAI 1 lumped 91 585	-65.72	-85.32	-80.16	-83.33	-88.17	-81.20	-73.54	-78.63	-85.09	-91.09
TAI 1 lumped 96 585	-68.95	-85.64	-79.95	-83.17	-87.64	-81.40	-74.50	-77.63	-84.42	-90.36
TAI 2 semi 86 585	-66.02	-85.23	-80.06	-84.16	-88.12	-80.86	-73.56	-79.33	-86.57	-92.27
TAI 2 semi 91 585	-66.02	-85.23	-79.16	-83.81	-88.01	-80.62	-73.48	-78.28	-85.80	-91.38
TAI 2 semi 96 585	-68.12	-85.80	-79.40	-83.36	-87.48	-80.78	-73.81	-77.19	-85.32	-90.94
TAI 3 snow 96 585	-68.71	-85.78	-80.08	-83.13	-87.31	-81.35	-74.60	-77.40	-84.73	-90.50
TAI 3 snow 01 585	-66.76	-85.80	-80.07	-84.15	-87.41	-81.85	-74.48	-77.43	-85.31	-91.00
TAI 4 distributed 86 585	-68.08	-84.66	-80.05	-83.32	-88.45	-79.81	-74.36	-79.50	-86.76	-93.18
TAI 4 distributed 91 585	-69.40	-84.71	-78.91	-84.62	-88.68	-80.36	-74.48	-78.68	-85.73	-92.35
TAI 4 distributed 96 585	-71.35	-85.85	-78.38	-84.10	-88.22	-81.47	-74.52	-77.59	-85.05	-91.27

Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%]

Variant	11	12	13	14	15	16	17	18	19	20
CMCC 1 lumped 86 126	-30.71	11.87	53.71	2.30	10.34	24.56	-15.81	5.63	-19.19	-9.90
CMCC 1 lumped 91 126	-28.41	16.56	62.30	6.71	10.88	22.93	-17.42	10.31	-15.54	-6.59
CMCC 1 lumped 96 126	-22.41	18.91	67.26	-2.29	15.88	14.71	-13.86	20.76	-18.78	-0.48
CMCC 2 semi 86 126	-34.28	5.78	54.01	0.14	9.06	29.94	-17.67	3.62	-18.58	-11.75
CMCC 2 semi 91 126	-32.17	9.78	59.07	0.82	10.70	25.37	-17.24	7.75	-16.08	-7.92
CMCC 2 semi 96 126	-24.33	15.47	69.15	-8.38	18.40	16.48	-14.61	20.61	-20.84	-0.02
CMCC 3 snow 96 126	-22.77	16.70	66.09	-3.84	19.72	15.26	-11.79	23.80	-16.94	1.06
CMCC 3 snow 01 126	-25.28	11.34	56.10	-5.85	15.56	17.24	-10.23	19.96	-20.53	-2.21
CMCC 4 distributed 86 126	-37.02	20.89	67.96	-0.25	8.36	26.83	-20.89	4.05	-19.82	-7.97
CMCC 4 distributed 91 126	-34.81	23.40	60.19	-3.39	12.91	20.37	-16.55	11.72	-20.64	-3.39
CMCC 4 distributed 96 126	-24.55	20.89	60.74	-11.34	19.10	11.04	-11.83	25.81	-23.72	-0.43
EC 1 lumped 86 126	-36.86	-6.42	30.23	-5.01	10.06	13.11	-23.48	-12.54	-18.78	-14.53
EC 1 lumped 91 126	-34.60	-1.52	39.35	-0.20	10.83	13.38	-24.36	-8.94	-15.47	-10.34
EC 1 lumped 96 126	-26.13	1.41	47.09	-6.58	17.93	7.97	-20.66	0.77	-17.02	-2.93
EC 2 semi 86 126	-41.57	-12.91	27.29	-7.97	7.38	16.48	-26.37	-16.01	-18.86	-17.46

Continued on next page

Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%] (Continuation)

Variant	11	12	13	14	15	16	17	18	19	20
EC 2 semi 91 126	-38.45	-8.36	33.55	-6.40	10.72	14.92	-24.98	-12.19	-15.88	-12.39
EC 2 semi 96 126	-29.77	-3.11	46.04	-13.24	19.71	8.20	-22.58	-1.48	-19.50	-3.56
EC 3 snow 96 126	-26.81	1.10	47.20	-7.35	22.53	8.96	-18.46	3.93	-14.70	-1.07
EC 3 snow 01 126	-32.06	-4.99	34.53	-10.24	17.21	8.53	-17.92	-1.08	-18.87	-5.94
EC 4 distributed 86 126	-44.08	-5.98	34.42	-11.56	5.56	10.20	-31.20	-18.15	-21.97	-14.87
EC 4 distributed 91 126	-41.56	0.35	34.90	-11.50	11.68	6.16	-25.14	-9.20	-21.76	-9.13
EC 4 distributed 96 126	-31.74	4.63	40.89	-16.15	17.58	3.46	-19.34	3.88	-22.71	-3.35
GFDL 1 lumped 86 126	-19.73	7.44	61.30	11.28	27.73	36.09	-1.56	14.36	-5.22	-6.12
GFDL 1 lumped 91 126	-18.40	10.77	67.69	15.33	28.35	33.42	-2.84	18.61	-2.11	-3.35
GFDL 1 lumped 96 126	-12.77	12.52	70.12	4.78	32.84	24.44	-0.53	28.22	-6.67	2.75
GFDL 2 semi 86 126	-23.03	1.55	62.50	9.90	28.14	41.45	-2.74	12.99	-3.12	-7.65
GFDL 2 semi 91 126	-20.72	5.16	66.36	10.56	30.44	37.05	-1.60	17.05	-0.73	-3.66
GFDL 2 semi 96 126	-14.83	8.69	72.34	-1.43	36.80	25.88	-1.22	28.02	-7.79	3.51
GFDL 3 snow 96 126	-13.41	10.81	69.49	3.05	37.68	24.93	1.59	31.39	-4.32	4.42
GFDL 3 snow 01 126	-14.51	6.86	61.83	2.14	35.15	27.79	3.92	28.61	-6.89	1.91
GFDL 4 distributed 86 126	-29.19	11.94	67.96	5.18	22.87	36.16	-8.95	9.67	-7.67	-6.04
GFDL 4 distributed 91 126	-26.79	16.64	64.28	3.30	29.64	30.87	-2.12	19.02	-7.84	-0.91
GFDL 4 distributed 96 126	-17.26	15.33	64.60	-5.73	34.21	23.45	2.44	32.32	-11.65	2.82
MPI 1 lumped 86 126	-19.98	10.44	61.70	12.17	29.76	36.39	-3.20	9.76	-4.52	-2.57
MPI 1 lumped 91 126	-18.84	13.76	67.41	16.08	30.08	33.02	-4.91	13.00	-1.76	-0.04
MPI 1 lumped 96 126	-13.19	13.97	69.76	5.28	33.77	23.00	-3.24	21.63	-6.25	5.55
MPI 2 semi 86 126	-23.56	4.35	62.10	10.59	29.90	42.12	-4.40	8.12	-2.39	-4.19
MPI 2 semi 91 126	-21.64	7.60	65.19	11.06	31.76	36.63	-3.60	11.48	-0.38	-0.62
MPI 2 semi 96 126	-15.55	9.36	71.08	-0.92	37.03	24.57	-3.92	21.34	-7.41	6.17
MPI 3 snow 96 126	-14.20	12.14	68.67	3.63	38.30	23.13	-1.35	24.64	-3.85	6.97
MPI 3 snow 01 126	-15.92	7.41	59.74	2.62	35.18	25.69	0.96	21.53	-6.53	4.11
MPI 4 distributed 86 126	-28.46	15.55	68.64	6.35	26.85	37.45	-9.46	6.18	-6.08	-0.88
MPI 4 distributed 91 126	-25.79	20.65	67.56	5.08	33.24	31.77	-2.78	15.99	-6.26	4.16
MPI 4 distributed 96 126	-17.02	18.12	66.58	-4.20	36.52	23.19	0.95	28.25	-10.17	6.67
MRI 1 lumped 86 126	-16.09	14.52	73.84	17.47	37.87	44.27	3.95	21.07	-2.70	1.14
MRI 1 lumped 91 126	-15.33	17.05	78.91	20.68	37.45	40.87	1.69	24.52	-0.04	3.18
MRI 1 lumped 96 126	-11.23	17.12	80.24	8.18	39.99	29.56	3.22	32.91	-5.28	8.20
MRI 2 semi 86 126	-19.78	8.26	74.95	15.58	38.86	50.42	2.82	19.86	-0.48	-0.35
MRI 2 semi 91 126	-18.13	11.02	77.74	15.43	39.86	44.99	3.48	23.41	1.41	2.95
MRI 2 semi 96 126	-13.60	12.77	82.08	1.46	44.18	30.91	2.70	33.15	-6.50	8.95

Continued on next page

Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%] (Continuation)

Variant	11	12	13	14	15	16	17	18	19	20
MRI 3 snow 96 126	-12.02	14.77	78.56	6.24	44.62	29.80	5.10	35.78	-3.01	9.62
MRI 3 snow 01 126	-13.11	10.37	70.15	5.13	41.88	32.45	7.51	32.88	-5.83	7.07
MRI 4 distributed 86 126	-25.31	19.78	80.75	11.80	34.12	44.91	-3.03	18.19	-4.12	1.87
MRI 4 distributed 91 126	-22.25	24.53	78.79	9.76	40.76	39.70	4.17	28.62	-4.20	7.04
MRI 4 distributed 96 126	-14.49	20.42	75.31	-1.57	43.99	29.48	7.70	40.74	-8.93	9.08
TAI 1 lumped 86 126	-26.02	12.76	55.43	9.92	26.05	31.53	-7.66	3.67	-8.19	-0.58
TAI 1 lumped 91 126	-23.34	18.33	64.84	15.54	27.58	29.87	-8.48	8.54	-4.44	3.55
TAI 1 lumped 96 126	-15.35	20.03	69.08	6.54	33.38	20.71	-5.42	18.86	-8.11	10.15
TAI 2 semi 86 126	-29.90	7.03	55.48	8.31	25.57	37.32	-9.21	1.74	-6.61	-1.74
TAI 2 semi 91 126	-27.06	11.92	61.10	9.88	28.67	32.56	-8.06	6.05	-3.97	3.05
TAI 2 semi 96 126	-18.07	16.32	70.81	0.33	36.98	22.34	-6.23	18.22	-9.49	11.43
TAI 3 snow 96 126	-16.29	18.67	68.06	5.00	37.85	20.87	-3.34	22.01	-6.07	11.71
TAI 3 snow 01 126	-20.51	12.99	57.30	2.34	33.16	22.23	-2.08	17.59	-9.65	7.67
TAI 4 distributed 86 126	-32.28	19.32	67.21	6.08	24.17	34.75	-12.75	1.23	-7.85	2.81
TAI 4 distributed 91 126	-30.86	23.96	62.59	4.39	30.21	28.64	-6.99	9.55	-8.84	7.60
TAI 4 distributed 96 126	-19.81	24.21	64.22	-2.87	34.93	19.95	-1.63	23.38	-12.16	11.01
CMCC 1 lumped 86 245	-30.24	11.49	52.72	8.04	18.48	29.22	-11.13	5.86	-12.28	-4.01
CMCC 1 lumped 91 245	-28.07	15.36	61.01	12.68	19.42	26.88	-12.80	10.18	-8.66	-0.77
CMCC 1 lumped 96 245	-22.06	16.80	64.98	3.40	24.03	17.73	-9.93	19.73	-12.47	5.18
CMCC 2 semi 86 245	-33.92	5.22	52.35	5.95	17.75	34.70	-12.94	3.88	-11.06	-5.40
CMCC 2 semi 91 245	-31.91	8.53	56.92	6.78	19.52	29.57	-12.55	7.55	-8.72	-1.60
CMCC 2 semi 96 245	-24.38	12.55	66.24	-2.82	26.84	19.23	-11.01	19.16	-14.14	6.11
CMCC 3 snow 96 245	-22.65	14.60	63.83	1.76	28.04	18.08	-8.03	22.62	-10.47	6.61
CMCC 3 snow 01 245	-25.20	9.58	53.98	-0.22	23.65	20.49	-6.38	18.82	-13.83	3.41
CMCC 4 distributed 86 245	-36.61	18.94	64.54	4.50	16.54	31.63	-16.54	4.00	-12.39	-1.28
CMCC 4 distributed 91 245	-34.68	22.26	59.28	1.87	22.00	25.00	-11.37	12.28	-13.26	3.38
CMCC 4 distributed 96 245	-24.52	19.39	59.70	-6.03	26.83	15.62	-6.95	25.38	-16.88	6.03
EC 1 lumped 86 245	-72.98	-58.76	-45.58	-59.33	-52.30	-49.41	-64.63	-60.80	-64.84	-62.72
EC 1 lumped 91 245	-71.97	-56.76	-41.51	-57.36	-52.16	-49.64	-65.14	-59.20	-63.51	-61.00
EC 1 lumped 96 245	-68.08	-54.95	-37.52	-59.47	-48.68	-52.02	-63.41	-54.72	-64.01	-57.41
EC 2 semi 86 245	-75.27	-62.02	-47.40	-61.07	-54.10	-48.07	-66.17	-62.64	-65.19	-64.29
EC 2 semi 91 245	-73.92	-60.13	-44.67	-60.37	-52.86	-49.10	-65.61	-60.92	-63.98	-62.19
EC 2 semi 96 245	-69.91	-57.24	-38.34	-62.54	-48.52	-51.90	-64.49	-56.07	-65.27	-57.82
EC 3 snow 96 245	-68.31	-55.15	-37.39	-59.73	-46.73	-51.52	-62.41	-53.19	-63.00	-56.62
EC 3 snow 01 245	-70.83	-57.90	-43.00	-61.07	-49.23	-51.36	-62.02	-55.55	-64.78	-58.60

Continued on next page

Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%] (Continuation)

Variant	11	12	13	14	15	16	17	18	19	20
EC 4 distributed 86 245	-76.17	-58.31	-42.90	-62.50	-54.58	-50.74	-68.22	-63.92	-66.40	-62.60
EC 4 distributed 91 245	-75.10	-55.71	-43.22	-62.53	-51.82	-52.93	-65.44	-59.83	-66.22	-60.09
EC 4 distributed 96 245	-70.34	-53.51	-39.42	-63.89	-48.82	-54.26	-62.75	-53.83	-66.72	-57.48
GFDL 1 lumped 86 245	-76.18	-67.72	-49.04	-67.44	-61.24	-58.85	-69.37	-62.02	-72.87	-71.59
GFDL 1 lumped 91 245	-75.94	-66.86	-47.19	-66.60	-61.32	-59.81	-69.95	-60.74	-71.89	-70.84
GFDL 1 lumped 96 245	-74.06	-65.93	-45.67	-69.61	-59.64	-62.30	-69.05	-57.53	-72.92	-68.66
GFDL 2 semi 86 245	-77.32	-69.56	-48.56	-68.18	-61.11	-57.25	-69.80	-62.39	-72.37	-72.14
GFDL 2 semi 91 245	-76.67	-68.38	-47.15	-68.06	-60.52	-58.41	-69.44	-60.88	-71.49	-70.84
GFDL 2 semi 96 245	-74.71	-66.93	-44.77	-71.54	-58.26	-61.77	-69.23	-57.21	-73.32	-68.38
GFDL 3 snow 96 245	-74.30	-66.34	-45.92	-70.03	-58.01	-61.98	-68.34	-56.40	-72.20	-68.06
GFDL 3 snow 01 245	-74.67	-67.46	-48.27	-70.27	-58.70	-60.93	-67.63	-57.22	-73.16	-68.78
GFDL 4 distributed 86 245	-78.97	-66.13	-46.64	-69.33	-62.91	-59.18	-71.86	-63.10	-73.67	-71.75
GFDL 4 distributed 91 245	-77.70	-64.62	-46.93	-69.74	-60.65	-60.37	-69.68	-59.54	-73.35	-69.89
GFDL 4 distributed 96 245	-74.90	-64.50	-46.69	-72.34	-58.66	-62.52	-68.16	-55.14	-74.18	-68.50
MPI 1 lumped 86 245	-78.06	-69.95	-53.10	-69.66	-64.14	-63.04	-74.28	-66.52	-75.39	-73.87
MPI 1 lumped 91 245	-77.71	-68.84	-51.37	-68.56	-63.75	-63.82	-74.60	-65.19	-74.40	-73.14
MPI 1 lumped 96 245	-76.26	-68.63	-50.88	-71.68	-62.54	-66.42	-74.09	-62.46	-75.74	-71.64
MPI 2 semi 86 245	-78.81	-71.15	-52.08	-69.89	-63.45	-61.37	-74.47	-66.49	-74.64	-73.94
MPI 2 semi 91 245	-78.25	-69.96	-51.04	-69.75	-62.69	-62.75	-74.20	-65.17	-74.01	-72.87
MPI 2 semi 96 245	-76.65	-69.26	-49.67	-73.23	-60.79	-65.94	-74.15	-61.86	-75.95	-71.10
MPI 3 snow 96 245	-76.63	-68.96	-51.44	-72.15	-61.16	-66.34	-73.61	-61.53	-75.22	-71.23
MPI 3 snow 01 245	-76.98	-70.02	-53.26	-72.47	-61.71	-65.58	-73.15	-62.26	-76.08	-71.82
MPI 4 distributed 86 245	-79.93	-68.20	-50.55	-70.54	-64.51	-62.26	-75.60	-66.27	-75.34	-73.29
MPI 4 distributed 91 245	-79.28	-66.88	-50.82	-71.03	-62.96	-63.42	-73.85	-63.66	-75.36	-71.89
MPI 4 distributed 96 245	-77.19	-67.26	-51.75	-73.81	-61.53	-65.74	-72.74	-59.76	-76.40	-71.23
MRI 1 lumped 86 245	-88.32	-82.82	-75.74	-82.30	-79.45	-78.01	-84.34	-82.35	-84.50	-84.32
MRI 1 lumped 91 245	-88.11	-82.36	-74.59	-81.73	-79.49	-78.63	-84.70	-81.80	-84.08	-83.92
MRI 1 lumped 96 245	-87.04	-81.88	-73.44	-83.09	-78.60	-80.06	-84.29	-80.21	-84.61	-82.76
MRI 2 semi 86 245	-89.16	-84.16	-76.29	-82.90	-79.94	-77.39	-84.82	-83.00	-84.49	-84.87
MRI 2 semi 91 245	-88.81	-83.68	-75.58	-82.82	-79.65	-78.24	-84.73	-82.43	-84.16	-84.28
MRI 2 semi 96 245	-87.71	-82.87	-73.67	-84.32	-78.48	-79.98	-84.68	-80.68	-85.06	-82.89
MRI 3 snow 96 245	-87.19	-82.13	-73.52	-83.28	-77.83	-79.95	-83.93	-79.65	-84.21	-82.52
MRI 3 snow 01 245	-87.79	-83.07	-75.39	-83.64	-78.62	-79.61	-83.61	-80.42	-84.79	-83.09
MRI 4 distributed 86 245	-90.01	-82.31	-74.79	-83.66	-80.49	-78.39	-85.93	-83.63	-85.07	-84.27
MRI 4 distributed 91 245	-89.46	-81.44	-74.98	-83.83	-79.28	-79.54	-84.78	-81.96	-85.03	-83.36

Continued on next page

Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%] (Continuation)

Variant	11	12	13	14	15	16	17	18	19	20
MRI 4 distributed 96 245	-87.94	-81.46	-74.11	-84.99	-78.55	-80.72	-84.11	-79.84	-85.67	-82.82
TAI 1 lumped 86 245	-89.25	-83.79	-77.84	-84.20	-81.39	-79.74	-85.73	-84.33	-86.18	-85.49
TAI 1 lumped 91 245	-88.95	-83.16	-76.60	-83.51	-81.30	-80.17	-85.94	-83.70	-85.70	-85.02
TAI 1 lumped 96 245	-87.77	-82.76	-75.68	-84.73	-80.40	-81.52	-85.50	-82.12	-86.22	-83.99
TAI 2 semi 86 245	-89.92	-84.89	-78.13	-84.64	-81.69	-78.99	-86.05	-84.79	-86.05	-85.85
TAI 2 semi 91 245	-89.55	-84.33	-77.40	-84.49	-81.36	-79.78	-85.93	-84.22	-85.72	-85.26
TAI 2 semi 96 245	-88.29	-83.56	-75.70	-85.80	-80.15	-81.35	-85.74	-82.41	-86.54	-83.99
TAI 3 snow 96 245	-87.88	-82.96	-75.75	-84.89	-79.70	-81.45	-85.18	-81.59	-85.87	-83.75
TAI 3 snow 01 245	-88.46	-83.82	-77.39	-85.26	-80.40	-81.15	-84.90	-82.29	-86.39	-84.31
TAI 4 distributed 86 245	-90.56	-83.15	-76.59	-85.18	-82.05	-79.64	-86.79	-85.11	-86.48	-85.24
TAI 4 distributed 91 245	-90.22	-82.38	-77.09	-85.39	-81.07	-80.64	-85.88	-83.72	-86.54	-84.42
TAI 4 distributed 96 245	-88.52	-82.33	-76.33	-86.35	-80.27	-81.84	-85.17	-81.57	-87.09	-83.94
CMCC 1 lumped 86 370	-49.67	-13.88	9.04	-17.25	-8.28	3.45	-34.55	-22.11	-31.05	-27.08
CMCC 1 lumped 91 370	-47.13	-10.21	18.41	-12.77	-7.06	2.15	-35.62	-18.32	-28.10	-23.62
CMCC 1 lumped 96 370	-39.94	-5.90	26.48	-17.04	-0.43	-3.02	-31.76	-8.41	-29.28	-16.72
CMCC 2 semi 86 370	-53.25	-20.30	6.45	-19.99	-10.98	7.12	-37.04	-25.13	-31.40	-29.45
CMCC 2 semi 91 370	-50.81	-17.31	12.16	-18.61	-8.84	3.73	-36.44	-21.78	-29.01	-25.76
CMCC 2 semi 96 370	-42.24	-10.04	26.16	-22.44	0.38	-1.56	-33.12	-9.80	-31.32	-16.79
CMCC 3 snow 96 370	-40.07	-7.39	26.65	-17.89	2.88	-2.38	-29.98	-5.60	-27.37	-15.20
CMCC 3 snow 01 370	-43.65	-13.05	15.77	-20.68	-2.41	-0.79	-29.25	-9.99	-30.94	-18.81
CMCC 4 distributed 86 370	-53.75	-7.95	22.14	-20.37	-10.27	5.64	-39.36	-24.78	-32.56	-25.23
CMCC 4 distributed 91 370	-52.42	-5.14	15.58	-22.44	-4.92	-1.00	-35.78	-18.21	-32.91	-20.90
CMCC 4 distributed 96 370	-40.69	-3.72	24.13	-25.07	2.09	-6.63	-30.55	-4.53	-34.20	-16.29
EC 1 lumped 86 370	-68.56	-54.51	-34.36	-54.18	-46.29	-45.02	-62.19	-52.47	-60.43	-59.04
EC 1 lumped 91 370	-67.71	-52.16	-29.97	-52.16	-46.10	-45.14	-62.72	-50.63	-58.69	-57.11
EC 1 lumped 96 370	-63.60	-50.14	-25.96	-55.45	-42.26	-47.56	-60.92	-45.10	-59.60	-53.35
EC 2 semi 86 370	-70.71	-57.55	-35.03	-55.47	-47.33	-43.28	-63.28	-53.78	-60.04	-60.33
EC 2 semi 91 370	-69.22	-55.08	-31.66	-54.74	-45.64	-43.94	-62.49	-51.48	-58.40	-57.72
EC 2 semi 96 370	-65.09	-51.86	-25.57	-58.39	-40.89	-47.22	-61.38	-45.25	-60.41	-53.33
EC 3 snow 96 370	-64.03	-50.17	-25.91	-55.83	-39.83	-47.00	-59.82	-43.37	-58.46	-52.38
EC 3 snow 01 370	-66.25	-52.87	-31.38	-56.89	-41.89	-46.93	-59.30	-45.37	-60.44	-54.42
EC 4 distributed 86 370	-71.89	-54.09	-31.59	-56.97	-48.40	-46.22	-65.71	-54.46	-61.47	-59.35
EC 4 distributed 91 370	-70.35	-50.93	-31.46	-57.23	-45.11	-47.84	-62.67	-49.70	-61.42	-56.21
EC 4 distributed 96 370	-65.97	-48.20	-28.44	-59.74	-41.75	-49.01	-59.77	-42.39	-61.95	-53.30
GFDL 1 lumped 86 370	-76.89	-66.66	-52.25	-66.34	-61.62	-59.08	-70.34	-65.68	-71.60	-70.94

Continued on next page

Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%] (Continuation)

Variant	11	12	13	14	15	16	17	18	19	20
GFDL 1 lumped 91 370	-76.39	-65.51	-49.72	-65.08	-61.42	-59.87	-70.86	-64.37	-70.50	-69.86
GFDL 1 lumped 96 370	-74.34	-64.80	-48.13	-67.94	-59.72	-62.54	-69.97	-61.34	-71.62	-67.61
GFDL 2 semi 86 370	-78.15	-68.63	-52.30	-67.13	-61.94	-57.62	-71.01	-66.42	-71.25	-71.52
GFDL 2 semi 91 370	-77.43	-67.38	-50.58	-66.87	-61.18	-58.92	-70.75	-65.11	-70.33	-70.08
GFDL 2 semi 96 370	-75.16	-66.11	-47.66	-70.06	-58.87	-62.17	-70.44	-61.68	-72.18	-67.43
GFDL 3 snow 96 370	-74.55	-65.28	-48.29	-68.40	-58.20	-62.34	-69.28	-60.35	-70.88	-67.04
GFDL 3 snow 01 370	-75.36	-66.70	-51.23	-68.96	-59.46	-61.59	-68.71	-61.48	-71.96	-68.11
GFDL 4 distributed 86 370	-79.60	-65.06	-49.46	-68.31	-63.17	-59.21	-72.73	-67.30	-72.53	-70.92
GFDL 4 distributed 91 370	-78.71	-63.68	-50.67	-68.82	-61.00	-60.97	-70.73	-64.33	-72.40	-69.12
GFDL 4 distributed 96 370	-75.60	-63.73	-49.84	-71.15	-59.29	-63.36	-69.23	-60.15	-73.27	-67.64
MPI 1 lumped 86 370	-81.38	-72.63	-60.62	-72.35	-68.96	-67.24	-76.88	-72.48	-76.93	-76.39
MPI 1 lumped 91 370	-80.98	-71.71	-58.77	-71.31	-68.77	-67.92	-77.31	-71.45	-76.05	-75.64
MPI 1 lumped 96 370	-79.58	-71.44	-57.94	-73.89	-67.72	-70.20	-76.75	-69.14	-77.11	-74.18
MPI 2 semi 86 370	-82.33	-74.13	-60.60	-72.82	-69.06	-65.92	-77.34	-72.99	-76.52	-76.76
MPI 2 semi 91 370	-81.82	-73.23	-59.46	-72.65	-68.55	-67.09	-77.19	-72.00	-75.87	-75.77
MPI 2 semi 96 370	-80.20	-72.52	-57.58	-75.49	-66.99	-69.91	-77.09	-69.31	-77.49	-74.01
MPI 3 snow 96 370	-79.78	-71.91	-58.20	-74.30	-66.60	-70.11	-76.26	-68.37	-76.56	-73.82
MPI 3 snow 01 370	-80.44	-73.18	-60.69	-74.76	-67.67	-69.65	-75.86	-69.36	-77.44	-74.64
MPI 4 distributed 86 370	-83.40	-71.10	-58.30	-73.66	-69.79	-67.03	-78.54	-73.32	-77.29	-76.03
MPI 4 distributed 91 370	-82.65	-70.02	-58.96	-74.12	-68.14	-68.43	-77.04	-70.92	-77.35	-74.74
MPI 4 distributed 96 370	-80.51	-70.56	-59.11	-76.31	-67.15	-70.48	-76.00	-67.69	-78.22	-74.02
MRI 1 lumped 86 370	-84.42	-79.06	-68.64	-77.85	-74.04	-72.84	-80.79	-78.45	-81.50	-81.12
MRI 1 lumped 91 370	-84.22	-78.43	-67.47	-77.13	-73.98	-73.49	-81.12	-77.79	-80.97	-80.59
MRI 1 lumped 96 370	-83.06	-78.20	-66.83	-79.22	-73.24	-75.46	-80.70	-76.12	-81.76	-79.39
MRI 2 semi 86 370	-85.18	-80.29	-68.66	-78.25	-74.02	-71.75	-81.05	-78.80	-81.19	-81.49
MRI 2 semi 91 370	-84.81	-79.64	-67.97	-78.19	-73.66	-72.78	-80.88	-78.14	-80.78	-80.75
MRI 2 semi 96 370	-83.55	-79.08	-66.58	-80.53	-72.60	-75.17	-80.85	-76.24	-82.05	-79.29
MRI 3 snow 96 370	-83.22	-78.52	-67.00	-79.54	-72.28	-75.41	-80.29	-75.55	-81.27	-79.07
MRI 3 snow 01 370	-83.55	-79.40	-68.69	-79.77	-72.88	-74.89	-79.83	-76.14	-81.78	-79.63
MRI 4 distributed 86 370	-86.19	-78.18	-67.57	-79.14	-75.00	-72.85	-82.27	-79.34	-82.04	-81.01
MRI 4 distributed 91 370	-85.77	-77.28	-67.89	-79.49	-73.67	-74.02	-80.98	-77.44	-82.05	-80.07
MRI 4 distributed 96 370	-83.92	-77.52	-67.78	-81.29	-72.98	-75.67	-80.17	-75.12	-82.71	-79.40
TAI 1 lumped 86 370	-88.31	-80.77	-72.95	-81.93	-79.70	-78.23	-85.51	-82.02	-85.01	-83.45
TAI 1 lumped 91 370	-87.76	-79.74	-71.14	-80.93	-79.30	-78.62	-85.61	-80.98	-84.31	-82.74
TAI 1 lumped 96 370	-86.36	-79.17	-70.28	-82.39	-78.14	-80.06	-84.98	-78.90	-84.93	-81.59

Continued on next page

Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%] (Continuation)

Variant	11	12	13	14	15	16	17	18	19	20
TAI 2 semi 86 370	-88.93	-81.72	-72.75	-82.18	-79.68	-77.30	-85.77	-82.28	-84.74	-83.58
TAI 2 semi 91 370	-88.45	-80.80	-71.68	-81.93	-79.10	-78.21	-85.61	-81.43	-84.30	-82.81
TAI 2 semi 96 370	-86.71	-79.67	-69.74	-83.46	-77.36	-79.78	-85.07	-78.83	-85.16	-81.30
TAI 3 snow 96 370	-86.46	-79.40	-70.38	-82.67	-77.33	-80.03	-84.61	-78.31	-84.63	-81.30
TAI 3 snow 01 370	-87.12	-80.41	-72.12	-83.16	-78.06	-79.70	-84.45	-79.06	-85.26	-81.94
TAI 4 distributed 86 370	-89.24	-79.42	-70.62	-82.32	-79.95	-77.50	-86.32	-82.15	-84.69	-82.86
TAI 4 distributed 91 370	-89.15	-78.79	-71.88	-82.78	-79.02	-78.63	-85.61	-81.01	-84.93	-82.10
TAI 4 distributed 96 370	-87.05	-78.72	-71.49	-84.08	-77.90	-80.40	-84.70	-78.26	-85.64	-81.57
CMCC 1 lumped 86 585	-39.75	-3.48	31.29	-8.09	1.88	13.89	-25.99	-6.43	-25.32	-21.83
CMCC 1 lumped 91 585	-37.16	0.72	40.32	-3.67	2.87	12.06	-27.49	-2.05	-22.12	-18.83
CMCC 1 lumped 96 585	-30.19	4.49	46.71	-10.61	8.20	4.89	-24.09	8.27	-24.78	-12.61
CMCC 2 semi 86 585	-43.68	-10.15	29.70	-10.86	0.01	18.14	-28.45	-9.63	-25.38	-24.37
CMCC 2 semi 91 585	-41.40	-6.64	35.10	-9.94	1.66	13.84	-28.15	-5.91	-23.26	-21.06
CMCC 2 semi 96 585	-32.74	0.15	47.29	-16.66	9.80	6.05	-25.48	6.71	-27.17	-12.92
CMCC 3 snow 96 585	-30.45	2.89	46.18	-11.81	11.90	5.22	-22.24	11.27	-23.03	-11.28
CMCC 3 snow 01 585	-34.12	-2.99	35.47	-14.18	6.94	7.15	-21.33	6.67	-26.62	-14.60
CMCC 4 distributed 86 585	-45.45	3.23	42.91	-11.47	-0.11	16.26	-31.26	-9.55	-26.59	-20.17
CMCC 4 distributed 91 585	-43.94	5.98	36.98	-13.97	5.07	9.48	-27.43	-2.16	-27.27	-15.95
CMCC 4 distributed 96 585	-33.09	6.58	41.88	-19.37	11.18	1.44	-22.95	11.98	-29.98	-12.70
EC 1 lumped 86 585	-74.27	-59.75	-46.88	-60.61	-53.62	-52.24	-65.68	-62.08	-65.08	-63.02
EC 1 lumped 91 585	-73.45	-57.84	-42.77	-58.85	-53.62	-52.56	-66.14	-60.62	-63.79	-61.20
EC 1 lumped 96 585	-69.35	-55.92	-38.17	-60.89	-49.86	-54.33	-64.29	-55.89	-64.04	-57.17
EC 2 semi 86 585	-76.41	-62.94	-48.38	-62.14	-55.43	-51.07	-67.05	-63.77	-65.35	-64.57
EC 2 semi 91 585	-75.09	-61.05	-45.46	-61.49	-54.11	-51.80	-66.34	-62.02	-63.97	-62.24
EC 2 semi 96 585	-71.06	-58.10	-38.77	-63.75	-49.61	-54.22	-65.13	-56.95	-65.11	-57.45
EC 3 snow 96 585	-69.56	-56.05	-37.75	-61.04	-47.80	-53.70	-63.20	-54.30	-62.85	-56.22
EC 3 snow 01 585	-71.87	-58.59	-43.11	-62.16	-50.01	-53.53	-62.60	-56.42	-64.54	-58.19
EC 4 distributed 86 585	-76.97	-59.82	-44.40	-63.82	-56.22	-54.17	-69.74	-65.02	-66.80	-63.30
EC 4 distributed 91 585	-75.71	-56.75	-43.95	-63.53	-53.11	-55.84	-66.88	-60.59	-66.32	-60.34
EC 4 distributed 96 585	-70.81	-54.34	-38.97	-64.96	-49.61	-56.43	-63.96	-54.20	-66.42	-57.04
GFDL 1 lumped 86 585	-69.38	-57.04	-34.88	-58.15	-52.14	-47.89	-63.22	-55.08	-65.80	-63.68
GFDL 1 lumped 91 585	-68.90	-55.70	-32.77	-56.70	-52.09	-48.83	-63.69	-53.32	-64.62	-62.80
GFDL 1 lumped 96 585	-67.25	-55.66	-32.64	-61.25	-51.05	-52.85	-62.94	-49.98	-66.46	-60.97
GFDL 2 semi 86 585	-70.40	-58.85	-33.42	-58.58	-51.49	-45.37	-63.42	-55.17	-64.82	-63.83
GFDL 2 semi 91 585	-69.78	-57.58	-32.44	-58.60	-51.09	-47.34	-63.15	-53.70	-64.06	-62.61

Continued on next page

Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%] (Continuation)

Variant	11	12	13	14	15	16	17	18	19	20
GFDL 2 semi 96 585	-67.80	-56.73	-31.18	-63.58	-49.17	-52.19	-63.03	-49.68	-66.71	-60.34
GFDL 3 snow 96 585	-67.47	-56.52	-33.24	-61.99	-49.31	-52.71	-62.25	-48.86	-65.67	-60.38
GFDL 3 snow 01 585	-67.42	-57.73	-35.48	-62.31	-49.86	-51.32	-61.31	-49.65	-66.54	-61.05
GFDL 4 distributed 86 585	-72.42	-54.39	-31.51	-59.59	-53.26	-47.31	-65.38	-55.45	-65.99	-63.14
GFDL 4 distributed 91 585	-71.60	-52.90	-33.05	-60.52	-51.45	-48.94	-62.98	-51.91	-66.03	-61.43
GFDL 4 distributed 96 585	-68.23	-54.64	-34.76	-64.81	-49.79	-52.78	-61.56	-47.18	-67.69	-60.64
MPI 1 lumped 86 585	-80.66	-72.96	-61.56	-72.82	-68.76	-67.02	-76.71	-73.90	-76.99	-76.29
MPI 1 lumped 91 585	-80.26	-71.97	-59.75	-71.71	-68.54	-67.65	-77.10	-73.00	-76.22	-75.52
MPI 1 lumped 96 585	-78.71	-71.69	-58.91	-74.16	-67.48	-69.87	-76.52	-70.70	-77.18	-74.03
MPI 2 semi 86 585	-81.56	-74.46	-61.55	-73.21	-68.83	-65.63	-77.10	-74.30	-76.50	-76.72
MPI 2 semi 91 585	-81.02	-73.52	-60.48	-72.99	-68.28	-66.82	-76.91	-73.39	-75.89	-75.73
MPI 2 semi 96 585	-79.26	-72.77	-58.57	-75.65	-66.76	-69.44	-76.76	-70.72	-77.44	-73.90
MPI 3 snow 96 585	-78.92	-72.11	-59.13	-74.54	-66.37	-69.80	-76.05	-69.94	-76.57	-73.67
MPI 3 snow 01 585	-79.47	-73.36	-61.54	-74.91	-67.34	-69.23	-75.55	-70.81	-77.30	-74.49
MPI 4 distributed 86 585	-82.58	-71.44	-59.28	-73.95	-69.42	-66.60	-78.18	-74.54	-77.31	-75.78
MPI 4 distributed 91 585	-81.99	-70.29	-59.89	-74.40	-67.80	-68.00	-76.67	-72.25	-77.43	-74.55
MPI 4 distributed 96 585	-79.61	-70.59	-59.71	-76.38	-66.82	-69.91	-75.58	-68.94	-78.15	-73.75
MRI 1 lumped 86 585	-88.26	-83.19	-75.47	-82.56	-79.06	-78.42	-84.81	-82.27	-85.26	-84.87
MRI 1 lumped 91 585	-88.01	-82.60	-74.14	-81.99	-79.10	-78.89	-85.13	-81.64	-84.81	-84.40
MRI 1 lumped 96 585	-86.70	-82.00	-72.73	-83.30	-77.94	-80.14	-84.62	-79.84	-85.28	-83.16
MRI 2 semi 86 585	-89.09	-84.43	-75.84	-83.14	-79.44	-77.76	-85.22	-82.86	-85.26	-85.41
MRI 2 semi 91 585	-88.68	-83.79	-74.93	-83.02	-79.05	-78.40	-85.06	-82.17	-84.86	-84.73
MRI 2 semi 96 585	-87.33	-82.80	-72.72	-84.48	-77.57	-80.01	-84.86	-80.16	-85.71	-83.25
MRI 3 snow 96 585	-86.87	-82.14	-72.76	-83.48	-77.09	-80.02	-84.21	-79.24	-84.91	-82.90
MRI 3 snow 01 585	-87.54	-83.05	-74.62	-83.83	-77.80	-79.72	-83.86	-79.97	-85.49	-83.48
MRI 4 distributed 86 585	-89.72	-82.59	-74.37	-83.78	-80.02	-78.69	-86.29	-83.38	-85.79	-84.82
MRI 4 distributed 91 585	-89.24	-81.73	-74.48	-83.93	-78.76	-79.62	-85.18	-81.66	-85.72	-83.83
MRI 4 distributed 96 585	-87.51	-81.31	-73.28	-85.03	-77.67	-80.58	-84.34	-79.28	-86.21	-83.14
TAI 1 lumped 86 585	-86.67	-79.95	-70.81	-79.73	-76.42	-75.49	-83.46	-81.44	-82.61	-81.97
TAI 1 lumped 91 585	-86.17	-78.82	-68.98	-78.62	-76.07	-75.75	-83.53	-80.38	-81.87	-81.19
TAI 1 lumped 96 585	-84.75	-78.44	-68.23	-80.39	-74.89	-77.64	-83.00	-78.35	-82.64	-80.01
TAI 2 semi 86 585	-87.16	-80.65	-70.07	-79.70	-76.11	-74.23	-83.59	-81.45	-82.10	-81.93
TAI 2 semi 91 585	-86.63	-79.63	-69.05	-79.44	-75.47	-75.18	-83.37	-80.58	-81.61	-81.05
TAI 2 semi 96 585	-84.96	-78.63	-67.32	-81.37	-73.75	-77.22	-82.99	-78.07	-82.66	-79.52
TAI 3 snow 96 585	-84.85	-78.66	-68.30	-80.70	-73.96	-77.65	-82.62	-77.76	-82.27	-79.71

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Tab. 6.53: Changes in discharge for annual runoff for mean over 30 years (2/3) [%] (Continuation)

Variant	11	12	13	14	15	16	17	18	19	20
TAI 3 snow 01 585	-85.39	-79.48	-69.90	-81.15	-74.54	-77.30	-82.32	-78.42	-82.78	-80.31
TAI 4 distributed 86 585	-87.59	-78.59	-68.23	-80.09	-76.66	-74.63	-84.37	-81.45	-82.31	-81.22
TAI 4 distributed 91 585	-87.69	-77.75	-69.50	-80.55	-75.75	-75.61	-83.42	-80.35	-82.53	-80.45
TAI 4 distributed 96 585	-85.56	-77.77	-69.29	-82.25	-74.72	-77.64	-82.52	-77.67	-83.36	-79.88

Tab. 6.54: Changes in discharge for annual runoff for mean over 30 years (3/3) [%]

Variant	21	22	23	24	25	26	27	28	29	30
CMCC 1 lumped 86 126	-32.83	6.91	-7.07	61.80	-22.96	7.62	-46.96	-25.95	52.37	180.72
CMCC 1 lumped 91 126	-30.14	8.30	-6.66	66.35	-20.11	9.78	-45.07	-23.13	57.55	176.25
CMCC 1 lumped 96 126	-25.15	20.00	-7.76	65.91	-18.61	15.84	-36.85	-20.91	73.48	167.17
CMCC 2 semi 86 126	-30.74	6.98	-6.39	70.91	-22.95	8.19	-50.44	-24.39	57.64	218.31
CMCC 2 semi 91 126	-29.06	12.41	-6.25	75.66	-20.06	9.64	-47.33	-21.28	63.18	200.58
CMCC 2 semi 96 126	-24.27	26.35	-7.18	76.04	-17.68	18.15	-37.63	-19.02	86.55	195.37
CMCC 3 snow 96 126	-23.28	24.32	-7.24	67.84	-15.65	21.96	-34.18	-16.97	77.66	178.71
CMCC 3 snow 01 126	-25.64	27.34	-8.59	69.67	-20.38	20.40	-36.48	-21.44	76.88	188.21
CMCC 4 distributed 86 126	-33.24	3.95	-2.18	76.06	-16.84	12.75	-48.90	-24.03	56.16	239.41
CMCC 4 distributed 91 126	-35.07	9.01	-3.87	80.19	-14.77	8.34	-46.50	-29.05	60.20	208.98
CMCC 4 distributed 96 126	-29.45	29.98	-9.54	70.42	-15.19	18.13	-37.46	-24.12	83.74	183.84
EC 1 lumped 86 126	-36.76	-7.44	-16.09	47.82	-23.86	3.89	-53.30	-31.88	52.40	180.69
EC 1 lumped 91 126	-33.77	-6.13	-15.89	54.04	-20.59	8.44	-51.24	-29.57	58.24	176.21
EC 1 lumped 96 126	-27.74	5.87	-15.24	56.17	-16.49	18.03	-43.64	-26.28	76.55	173.67
EC 2 semi 86 126	-35.72	-9.05	-17.27	55.24	-24.73	4.24	-57.36	-31.56	56.85	213.36
EC 2 semi 91 126	-33.18	-3.55	-15.68	62.45	-20.98	8.55	-54.14	-27.97	64.08	199.07
EC 2 semi 96 126	-27.95	9.60	-16.18	64.54	-16.29	19.51	-45.46	-25.10	89.46	199.66
EC 3 snow 96 126	-25.56	9.64	-13.65	58.43	-12.95	24.36	-40.76	-22.11	81.23	184.98
EC 3 snow 01 126	-29.15	10.33	-14.87	58.54	-19.07	20.62	-44.21	-26.73	79.07	191.32
EC 4 distributed 86 126	-39.30	-12.95	-16.39	54.24	-20.53	5.84	-56.92	-34.31	52.68	230.76
EC 4 distributed 91 126	-39.46	-5.88	-17.43	61.60	-16.43	4.29	-53.71	-37.78	57.46	207.20
EC 4 distributed 96 126	-32.38	14.60	-19.74	60.52	-14.67	19.87	-45.00	-30.77	85.34	185.16
GFDL 1 lumped 86 126	-19.78	15.18	-5.47	66.98	-11.55	22.03	-47.49	-19.72	85.58	229.18

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Tab. 6.54: Changes in discharge for annual runoff for mean over 30 years (3/3) [%] (Continuation)

Variant	21	22	23	24	25	26	27	28	29	30
GFDL 1 lumped 91 126	-17.94	16.44	-5.84	70.07	-9.43	24.88	-46.24	-17.58	90.75	223.85
GFDL 1 lumped 96 126	-14.21	27.63	-6.84	67.24	-8.10	31.67	-38.91	-15.83	105.83	214.21
GFDL 2 semi 86 126	-17.09	16.30	-5.57	77.40	-10.86	24.26	-50.89	-18.08	95.39	276.20
GFDL 2 semi 91 126	-15.67	22.64	-5.19	81.62	-8.29	27.06	-48.02	-15.05	101.85	257.16
GFDL 2 semi 96 126	-13.36	35.24	-7.43	77.77	-6.73	35.51	-39.83	-14.07	123.61	248.86
GFDL 3 snow 96 126	-12.11	32.38	-6.16	69.06	-4.83	38.79	-36.12	-11.64	110.35	227.86
GFDL 3 snow 01 126	-12.76	37.46	-7.33	73.94	-8.61	38.51	-37.51	-15.46	113.31	243.61
GFDL 4 distributed 86 126	-22.79	8.71	-3.09	77.66	-6.24	26.72	-51.03	-21.31	89.01	297.09
GFDL 4 distributed 91 126	-24.74	14.83	-2.41	83.31	-3.71	23.47	-48.11	-25.31	95.57	268.60
GFDL 4 distributed 96 126	-19.63	37.04	-9.34	73.54	-4.36	36.38	-39.61	-20.14	120.65	240.20
MPI 1 lumped 86 126	-20.78	10.81	-3.44	77.51	-9.28	25.53	-45.66	-19.00	90.55	230.04
MPI 1 lumped 91 126	-19.39	11.26	-3.96	80.59	-7.33	28.49	-44.58	-17.17	95.79	223.78
MPI 1 lumped 96 126	-16.39	21.59	-5.22	76.07	-5.84	35.13	-37.79	-15.37	110.21	213.63
MPI 2 semi 86 126	-18.02	10.91	-3.27	89.21	-8.56	27.73	-49.36	-17.28	101.23	276.33
MPI 2 semi 91 126	-17.23	16.35	-3.02	92.79	-6.19	30.32	-46.92	-14.42	107.60	255.94
MPI 2 semi 96 126	-15.65	27.62	-5.42	87.39	-4.40	38.57	-39.20	-13.34	129.06	247.44
MPI 3 snow 96 126	-14.61	25.63	-4.17	77.72	-2.50	42.17	-35.21	-11.00	114.57	226.17
MPI 3 snow 01 126	-15.79	29.73	-5.19	82.81	-6.59	41.73	-36.96	-14.77	117.93	241.05
MPI 4 distributed 86 126	-22.14	5.48	-1.70	90.46	-2.79	30.91	-48.32	-20.61	96.95	302.42
MPI 4 distributed 91 126	-24.15	12.22	-1.44	96.61	-0.23	27.44	-45.38	-24.56	103.36	273.82
MPI 4 distributed 96 126	-20.67	32.62	-7.28	84.86	-0.96	40.26	-37.53	-18.81	127.55	242.55
MRI 1 lumped 86 126	-13.95	23.68	1.18	78.69	-8.39	29.62	-41.66	-16.72	93.69	245.23
MRI 1 lumped 91 126	-12.86	24.01	0.50	80.13	-6.81	31.63	-40.57	-15.08	97.82	238.15
MRI 1 lumped 96 126	-10.41	33.73	-1.48	74.39	-5.82	37.66	-33.72	-13.89	111.50	225.43
MRI 2 semi 86 126	-10.85	24.60	1.65	90.25	-7.81	31.96	-45.25	-15.00	103.64	296.04
MRI 2 semi 91 126	-10.18	30.08	1.65	92.59	-5.55	34.08	-42.59	-12.50	109.38	274.63
MRI 2 semi 96 126	-9.36	41.06	-1.55	85.32	-4.36	41.46	-35.03	-12.13	129.35	262.52
MRI 3 snow 96 126	-8.36	38.13	-0.91	75.83	-2.63	45.00	-31.04	-9.68	115.54	239.41
MRI 3 snow 01 126	-8.99	42.91	-2.19	80.55	-6.50	44.49	-32.61	-13.70	118.85	255.05
MRI 4 distributed 86 126	-15.92	17.76	3.99	90.34	-2.23	34.64	-44.98	-18.38	97.47	320.49
MRI 4 distributed 91 126	-18.12	24.73	4.84	96.21	0.59	30.79	-41.87	-22.61	104.69	291.16
MRI 4 distributed 96 126	-14.83	45.09	-2.58	81.26	-0.09	43.11	-34.00	-17.73	128.16	258.87
TAI 1 lumped 86 126	-24.49	8.52	-3.44	74.28	-12.30	19.95	-46.94	-20.70	76.05	221.29
TAI 1 lumped 91 126	-21.31	10.47	-3.02	80.11	-9.17	24.07	-44.75	-17.72	82.34	216.05
TAI 1 lumped 96 126	-16.10	23.21	-3.57	77.68	-7.25	31.55	-36.56	-15.07	98.96	208.25

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Tab. 6.54: Changes in discharge for annual runoff for mean over 30 years (3/3) [%] (Continuation)

Variant	21	22	23	24	25	26	27	28	29	30
TAI 2 semi 86 126	-21.78	8.56	-3.27	85.97	-11.67	22.06	-50.41	-18.71	83.81	265.21
TAI 2 semi 91 126	-19.68	14.99	-2.60	91.61	-8.67	25.12	-47.10	-14.98	90.50	245.47
TAI 2 semi 96 126	-15.12	29.63	-3.82	89.59	-5.91	34.93	-37.41	-12.62	115.37	241.10
TAI 3 snow 96 126	-14.22	27.62	-2.40	79.62	-3.93	38.23	-33.65	-10.79	103.54	220.68
TAI 3 snow 01 126	-17.24	30.72	-4.25	82.25	-9.46	35.68	-36.13	-15.40	103.09	231.95
TAI 4 distributed 86 126	-24.03	4.73	0.61	89.06	-5.22	26.31	-48.77	-19.92	81.96	287.78
TAI 4 distributed 91 126	-26.26	10.37	-0.23	95.95	-2.63	23.32	-46.34	-24.09	86.50	258.62
TAI 4 distributed 96 126	-20.50	33.89	-6.09	85.91	-3.37	35.97	-36.93	-18.20	111.84	230.72
CMCC 1 lumped 86 245	-27.56	10.11	-4.95	67.69	-18.34	14.73	-46.24	-24.00	63.21	197.65
CMCC 1 lumped 91 245	-25.09	11.26	-4.84	71.79	-15.69	17.04	-44.41	-21.28	68.47	192.22
CMCC 1 lumped 96 245	-20.48	22.48	-5.92	69.10	-13.99	23.39	-36.61	-19.06	83.97	183.74
CMCC 2 semi 86 245	-25.11	10.02	-4.39	77.66	-18.20	15.97	-49.77	-22.47	69.49	238.04
CMCC 2 semi 91 245	-23.71	15.40	-4.19	81.63	-15.58	17.48	-46.86	-19.25	75.02	218.61
CMCC 2 semi 96 245	-19.60	28.56	-5.71	79.56	-12.98	26.12	-37.77	-17.13	98.09	214.07
CMCC 3 snow 96 245	-18.64	26.67	-5.29	70.79	-11.04	29.80	-33.97	-15.08	88.14	195.79
CMCC 3 snow 01 245	-20.91	30.20	-6.43	73.84	-15.73	28.43	-36.19	-19.23	88.20	207.89
CMCC 4 distributed 86 245	-27.34	6.59	-1.19	82.66	-11.50	20.36	-48.12	-23.22	67.33	259.99
CMCC 4 distributed 91 245	-29.48	12.12	-2.01	87.39	-9.48	16.11	-45.67	-27.85	71.82	230.67
CMCC 4 distributed 96 245	-24.20	33.09	-8.16	75.86	-9.87	26.84	-36.86	-22.50	95.62	204.95
EC 1 lumped 86 245	-73.16	-58.90	-61.79	-35.29	-66.79	-53.48	-80.06	-69.79	-34.07	27.07
EC 1 lumped 91 245	-71.92	-58.53	-61.95	-32.55	-65.50	-51.62	-79.17	-68.83	-31.64	24.44
EC 1 lumped 96 245	-69.08	-52.58	-61.55	-31.10	-63.49	-47.08	-75.65	-67.06	-22.72	24.06
EC 2 semi 86 245	-72.90	-59.79	-62.41	-32.23	-67.39	-53.66	-82.02	-69.86	-32.72	41.10
EC 2 semi 91 245	-71.82	-57.36	-61.84	-29.03	-65.90	-51.93	-80.67	-68.24	-29.63	33.94
EC 2 semi 96 245	-69.33	-50.94	-61.94	-27.21	-63.55	-46.51	-76.61	-66.61	-17.21	35.36
EC 3 snow 96 245	-68.16	-50.76	-60.82	-29.95	-61.95	-44.15	-74.40	-65.16	-20.50	29.21
EC 3 snow 01 245	-69.79	-50.26	-61.11	-29.77	-64.63	-45.67	-75.86	-67.20	-21.37	32.48
EC 4 distributed 86 245	-74.02	-61.25	-62.06	-31.79	-65.31	-52.23	-81.57	-70.92	-34.18	48.03
EC 4 distributed 91 245	-74.20	-58.07	-62.66	-28.74	-63.63	-53.15	-80.17	-72.60	-32.25	37.36
EC 4 distributed 96 245	-70.72	-48.16	-63.83	-28.58	-62.72	-45.93	-76.06	-69.14	-18.75	28.49
GFDL 1 lumped 86 245	-75.10	-60.30	-70.44	-49.42	-73.34	-63.85	-82.29	-76.45	-44.81	2.35
GFDL 1 lumped 91 245	-74.78	-59.88	-70.45	-48.66	-72.64	-63.18	-81.85	-75.90	-43.57	-0.11
GFDL 1 lumped 96 245	-73.48	-55.98	-70.48	-48.99	-71.85	-60.51	-79.47	-75.19	-38.14	-2.23
GFDL 2 semi 86 245	-74.28	-59.66	-70.53	-46.49	-73.21	-63.42	-83.31	-76.07	-42.20	17.67
GFDL 2 semi 91 245	-73.83	-57.42	-70.23	-44.98	-72.23	-62.37	-82.26	-75.18	-40.18	11.82

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Tab. 6.54: Changes in discharge for annual runoff for mean over 30 years (3/3) [%] (Continuation)

Variant	21	22	23	24	25	26	27	28	29	30
GFDL 2 semi 96 245	-73.04	-52.96	-70.64	-45.79	-71.42	-59.35	-79.56	-74.69	-32.74	9.90
GFDL 3 snow 96 245	-72.70	-54.41	-70.24	-48.35	-70.82	-58.20	-78.47	-73.94	-36.64	2.32
GFDL 3 snow 01 245	-72.72	-52.45	-70.82	-46.91	-72.00	-58.23	-78.79	-75.18	-35.64	7.85
GFDL 4 distributed 86 245	-76.30	-62.30	-68.90	-46.26	-71.86	-62.60	-83.31	-76.73	-44.26	24.07
GFDL 4 distributed 91 245	-76.48	-59.88	-68.46	-43.97	-70.57	-63.47	-82.34	-77.89	-41.91	15.46
GFDL 4 distributed 96 245	-74.64	-52.36	-70.54	-46.64	-70.30	-58.87	-79.40	-76.19	-33.24	7.61
MPI 1 lumped 86 245	-77.11	-65.44	-74.20	-52.83	-76.30	-67.99	-83.75	-78.88	-52.11	-10.67
MPI 1 lumped 91 245	-76.61	-64.87	-74.03	-51.96	-75.68	-67.21	-83.23	-78.21	-50.93	-12.36
MPI 1 lumped 96 245	-75.64	-61.90	-74.21	-53.18	-75.39	-65.49	-81.22	-77.77	-47.25	-15.38
MPI 2 semi 86 245	-76.00	-64.77	-74.06	-49.41	-75.92	-67.26	-84.44	-78.25	-49.50	3.19
MPI 2 semi 91 245	-75.59	-62.86	-73.89	-48.38	-75.23	-66.52	-83.48	-77.50	-48.06	-2.19
MPI 2 semi 96 245	-74.97	-59.33	-74.29	-49.88	-74.88	-64.41	-81.16	-77.13	-42.62	-5.02
MPI 3 snow 96 245	-75.08	-60.69	-73.98	-52.74	-74.55	-63.66	-80.38	-76.68	-46.16	-11.82
MPI 3 snow 01 245	-75.10	-59.30	-74.73	-51.27	-75.58	-63.79	-80.71	-77.78	-45.36	-7.26
MPI 4 distributed 86 245	-77.31	-66.65	-72.45	-49.04	-74.38	-66.48	-84.19	-78.64	-50.61	9.54
MPI 4 distributed 91 245	-77.80	-64.71	-72.12	-46.91	-73.67	-67.19	-83.48	-79.52	-48.72	1.86
MPI 4 distributed 96 245	-76.63	-58.68	-73.80	-50.53	-73.82	-63.93	-80.98	-78.17	-42.89	-6.68
MRI 1 lumped 86 245	-87.98	-82.12	-83.81	-72.04	-85.54	-80.20	-91.36	-87.08	-70.65	-46.91
MRI 1 lumped 91 245	-87.75	-82.11	-83.98	-71.48	-85.26	-79.83	-91.15	-86.80	-69.92	-48.32
MRI 1 lumped 96 245	-87.02	-80.09	-84.02	-71.68	-84.80	-78.53	-89.88	-86.29	-66.94	-49.44
MRI 2 semi 86 245	-87.83	-82.38	-83.92	-70.58	-85.71	-80.17	-92.14	-87.05	-69.67	-40.36
MRI 2 semi 91 245	-87.67	-81.50	-83.83	-69.83	-85.30	-79.85	-91.71	-86.52	-68.69	-43.82
MRI 2 semi 96 245	-87.15	-79.31	-84.11	-70.06	-84.75	-78.23	-90.26	-86.12	-64.45	-44.53
MRI 3 snow 96 245	-86.71	-79.36	-83.80	-71.37	-84.23	-77.35	-89.42	-85.55	-66.10	-47.27
MRI 3 snow 01 245	-87.14	-78.81	-83.88	-70.86	-85.07	-77.59	-89.83	-86.26	-65.93	-45.15
MRI 4 distributed 86 245	-88.46	-83.24	-83.69	-70.18	-84.78	-79.61	-92.03	-87.57	-70.61	-37.72
MRI 4 distributed 91 245	-88.63	-82.08	-83.91	-69.41	-84.31	-80.30	-91.46	-88.28	-69.83	-42.34
MRI 4 distributed 96 245	-87.80	-78.39	-84.84	-70.68	-84.31	-78.03	-90.00	-87.19	-65.07	-46.89
TAI 1 lumped 86 245	-89.17	-83.36	-85.11	-73.98	-86.87	-81.79	-92.11	-88.17	-73.44	-50.96
TAI 1 lumped 91 245	-88.86	-83.17	-85.13	-73.24	-86.50	-81.30	-91.85	-87.81	-72.58	-51.88
TAI 1 lumped 96 245	-88.09	-81.15	-85.19	-73.51	-86.11	-80.06	-90.61	-87.39	-69.81	-52.74
TAI 2 semi 86 245	-88.90	-83.35	-85.16	-72.38	-86.90	-81.62	-92.73	-88.04	-72.38	-44.61
TAI 2 semi 91 245	-88.71	-82.41	-85.10	-71.60	-86.50	-81.24	-92.30	-87.54	-71.41	-47.68
TAI 2 semi 96 245	-88.10	-80.14	-85.29	-71.84	-86.01	-79.67	-90.84	-87.18	-67.38	-48.04
TAI 3 snow 96 245	-87.80	-80.43	-85.01	-73.20	-85.59	-78.99	-90.17	-86.74	-69.06	-50.76

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Tab. 6.54: Changes in discharge for annual runoff for mean over 30 years (3/3) [%] (Continuation)

Variant	21	22	23	24	25	26	27	28	29	30
TAI 3 snow 01 245	-88.21	-79.82	-85.24	-72.73	-86.38	-79.24	-90.52	-87.41	-68.94	-48.87
TAI 4 distributed 86 245	-89.38	-84.12	-84.67	-71.86	-86.01	-80.99	-92.50	-88.33	-72.93	-41.49
TAI 4 distributed 91 245	-89.62	-83.20	-84.75	-71.03	-85.61	-81.57	-92.09	-88.98	-72.24	-45.94
TAI 4 distributed 96 245	-88.76	-79.45	-85.68	-72.31	-85.63	-79.49	-90.63	-88.07	-67.92	-50.00
CMCC 1 humped 86 370	-49.09	-20.90	-23.98	26.25	-36.73	-10.71	-61.49	-37.98	20.27	126.46
CMCC 1 humped 91 370	-46.42	-19.75	-24.02	31.53	-33.82	-8.26	-59.48	-35.54	25.73	123.49
CMCC 1 humped 96 370	-40.55	-7.80	-23.25	34.52	-30.66	-0.91	-51.85	-32.24	42.87	122.88
CMCC 2 semi 86 370	-48.19	-22.28	-23.95	31.93	-37.47	-10.78	-65.06	-37.30	22.70	152.32
CMCC 2 semi 91 370	-46.30	-17.86	-23.50	37.46	-34.56	-8.99	-62.40	-34.12	28.42	139.37
CMCC 2 semi 96 370	-40.44	-4.03	-22.91	42.34	-30.19	0.88	-53.21	-30.58	52.99	144.18
CMCC 3 snow 96 370	-38.99	-4.19	-22.58	36.59	-27.90	4.38	-49.44	-28.68	46.72	132.48
CMCC 3 snow 01 370	-42.13	-3.03	-23.10	36.68	-32.62	2.12	-52.31	-32.52	44.05	138.36
CMCC 4 distributed 86 370	-48.73	-22.57	-21.72	38.99	-32.07	-5.94	-62.68	-37.33	23.17	170.42
CMCC 4 distributed 91 370	-50.20	-18.05	-23.76	41.20	-29.99	-9.81	-60.40	-41.57	25.75	146.00
CMCC 4 distributed 96 370	-42.71	2.11	-26.57	40.26	-28.89	1.60	-51.36	-35.52	51.92	132.45
EC 1 humped 86 370	-68.52	-50.00	-59.06	-27.91	-63.25	-51.28	-76.04	-67.05	-26.49	38.59
EC 1 humped 91 370	-67.30	-49.20	-58.77	-24.88	-61.72	-49.33	-75.07	-65.89	-23.86	35.97
EC 1 humped 96 370	-64.26	-42.67	-58.15	-23.47	-59.75	-44.44	-70.89	-64.39	-14.27	35.21
EC 2 semi 86 370	-67.76	-50.06	-59.58	-23.85	-63.49	-51.01	-77.90	-66.71	-24.00	55.89
EC 2 semi 91 370	-66.48	-46.74	-58.58	-19.95	-61.54	-48.87	-76.11	-64.90	-20.24	49.03
EC 2 semi 96 370	-63.92	-39.48	-58.54	-18.68	-59.41	-43.42	-71.34	-63.66	-7.25	49.42
EC 3 snow 96 370	-63.11	-40.59	-57.42	-22.26	-58.04	-41.32	-69.32	-62.45	-11.93	40.96
EC 3 snow 01 370	-64.39	-39.37	-58.30	-21.64	-60.78	-42.82	-70.69	-64.68	-12.57	45.10
EC 4 distributed 86 370	-69.76	-52.77	-57.92	-24.49	-61.60	-50.16	-77.64	-67.62	-25.79	63.63
EC 4 distributed 91 370	-69.60	-49.07	-57.84	-20.23	-59.49	-50.59	-76.03	-69.33	-23.09	52.89
EC 4 distributed 96 370	-66.24	-37.58	-59.26	-20.53	-58.70	-42.81	-71.11	-66.22	-8.78	42.26
GFDL 1 humped 86 370	-76.57	-63.59	-70.12	-48.35	-72.85	-62.80	-83.37	-76.00	-45.40	0.10
GFDL 1 humped 91 370	-75.88	-63.20	-70.14	-46.89	-71.92	-61.84	-82.85	-75.28	-43.74	-1.80
GFDL 1 humped 96 370	-74.42	-59.36	-70.31	-47.06	-71.17	-59.40	-80.42	-74.53	-38.50	-4.31
GFDL 2 semi 86 370	-76.03	-63.35	-70.19	-45.37	-72.76	-62.50	-84.51	-75.62	-43.12	13.93
GFDL 2 semi 91 370	-75.46	-61.30	-69.94	-43.47	-71.68	-61.48	-83.49	-74.56	-41.03	7.94
GFDL 2 semi 96 370	-74.39	-56.98	-70.48	-43.82	-70.79	-58.54	-80.72	-74.02	-33.61	6.14
GFDL 3 snow 96 370	-73.74	-57.84	-70.09	-46.46	-70.10	-57.17	-79.50	-73.27	-37.02	-0.10
GFDL 3 snow 01 370	-74.32	-56.38	-70.55	-45.51	-71.61	-57.65	-80.08	-74.57	-36.77	4.12
GFDL 4 distributed 86 370	-77.57	-65.42	-69.05	-44.84	-71.33	-61.50	-84.34	-76.19	-44.83	20.61

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Tab. 6.54: Changes in discharge for annual runoff for mean over 30 years (3/3) [%] (Continuation)

Variant	21	22	23	24	25	26	27	28	29	30
GFDL 4 distributed 91 370	-77.93	-63.42	-69.08	-42.72	-70.13	-62.54	-83.43	-77.54	-43.09	10.99
GFDL 4 distributed 96 370	-76.01	-56.16	-71.14	-45.05	-70.05	-58.22	-80.57	-75.83	-34.73	2.87
MPI 1 lumped 86 370	-81.27	-71.60	-75.68	-57.39	-78.38	-70.30	-86.50	-80.78	-56.45	-21.33
MPI 1 lumped 91 370	-80.77	-71.35	-75.70	-56.46	-77.73	-69.61	-86.11	-80.21	-55.21	-22.81
MPI 1 lumped 96 370	-79.80	-68.60	-75.95	-57.20	-77.29	-67.96	-84.28	-79.75	-51.44	-25.18
MPI 2 semi 86 370	-80.72	-71.52	-75.57	-54.78	-78.25	-69.94	-87.43	-80.41	-54.49	-10.44
MPI 2 semi 91 370	-80.38	-70.06	-75.46	-53.69	-77.55	-69.33	-86.69	-79.63	-52.97	-15.33
MPI 2 semi 96 370	-79.69	-66.93	-75.96	-54.53	-77.00	-67.28	-84.58	-79.29	-47.50	-17.16
MPI 3 snow 96 370	-79.32	-67.51	-75.77	-56.79	-76.50	-66.26	-83.58	-78.73	-50.36	-22.09
MPI 3 snow 01 370	-79.83	-66.53	-76.17	-55.99	-77.69	-66.62	-84.11	-79.82	-50.14	-18.84
MPI 4 distributed 86 370	-81.67	-72.86	-74.79	-54.07	-76.84	-69.09	-87.13	-80.91	-55.61	-4.59
MPI 4 distributed 91 370	-82.03	-71.24	-74.78	-52.54	-76.14	-70.01	-86.43	-81.96	-54.19	-11.95
MPI 4 distributed 96 370	-80.86	-65.94	-76.40	-55.35	-76.24	-66.96	-84.25	-80.64	-48.15	-19.07
MRI 1 lumped 86 370	-84.40	-77.79	-80.93	-66.34	-82.42	-75.25	-89.43	-84.07	-63.23	-34.22
MRI 1 lumped 91 370	-84.06	-77.69	-81.06	-65.78	-82.03	-74.69	-89.20	-83.73	-62.22	-35.57
MRI 1 lumped 96 370	-83.39	-75.59	-81.32	-66.52	-81.63	-73.30	-87.81	-83.34	-59.28	-37.53
MRI 2 semi 86 370	-83.92	-77.76	-80.90	-64.30	-82.36	-74.85	-90.18	-83.78	-61.38	-25.10
MRI 2 semi 91 370	-83.70	-76.68	-80.85	-63.57	-81.85	-74.32	-89.67	-83.24	-60.11	-29.16
MRI 2 semi 96 370	-83.28	-74.37	-81.33	-64.49	-81.37	-72.59	-88.12	-83.00	-55.82	-30.75
MRI 3 snow 96 370	-83.00	-74.74	-81.12	-66.19	-80.94	-71.86	-87.29	-82.47	-58.39	-34.84
MRI 3 snow 01 370	-83.24	-73.85	-81.26	-65.28	-81.73	-71.98	-87.65	-83.20	-57.76	-31.74
MRI 4 distributed 86 370	-84.90	-78.88	-80.60	-64.29	-81.39	-74.31	-90.14	-84.52	-62.60	-20.72
MRI 4 distributed 91 370	-85.29	-77.74	-80.58	-63.23	-80.81	-75.13	-89.54	-85.35	-61.42	-26.44
MRI 4 distributed 96 370	-84.40	-73.61	-81.89	-65.27	-80.77	-72.49	-87.94	-84.23	-56.48	-32.27
TAI 1 lumped 86 370	-87.82	-80.39	-83.65	-71.26	-86.01	-81.18	-90.78	-87.04	-72.91	-49.24
TAI 1 lumped 91 370	-87.22	-79.84	-83.50	-70.28	-85.47	-80.61	-90.29	-86.45	-71.75	-50.01
TAI 1 lumped 96 370	-86.16	-77.43	-83.52	-70.58	-85.12	-79.40	-88.69	-85.95	-68.87	-51.06
TAI 2 semi 86 370	-87.38	-80.18	-83.61	-69.39	-85.95	-80.88	-91.29	-86.73	-71.83	-42.22
TAI 2 semi 91 370	-86.99	-78.95	-83.53	-68.49	-85.46	-80.50	-90.64	-86.13	-70.76	-45.41
TAI 2 semi 96 370	-85.96	-75.98	-83.59	-68.62	-84.93	-78.83	-88.70	-85.61	-66.43	-45.61
TAI 3 snow 96 370	-85.81	-76.52	-83.44	-70.22	-84.60	-78.31	-88.15	-85.28	-68.12	-48.85
TAI 3 snow 01 370	-86.30	-75.85	-83.85	-69.88	-85.44	-78.72	-88.50	-86.08	-68.39	-46.97
TAI 4 distributed 86 370	-87.71	-80.86	-82.43	-68.46	-84.78	-79.99	-91.03	-86.61	-71.92	-38.96
TAI 4 distributed 91 370	-88.17	-80.21	-82.49	-67.53	-84.42	-80.62	-90.72	-87.29	-71.26	-44.27
TAI 4 distributed 96 370	-86.98	-75.86	-83.86	-69.41	-84.50	-78.76	-88.85	-86.46	-67.06	-48.26

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Tab. 6.54: Changes in discharge for annual runoff for mean over 30 years (3/3) [%] (Continuation)

Variant	21	22	23	24	25	26	27	28	29	30
CMCC 1 lumped 86 585	-43.51	-9.67	-16.12	44.74	-29.33	-4.53	-53.72	-32.56	33.33	151.08
CMCC 1 lumped 91 585	-41.03	-8.42	-15.77	49.61	-26.64	-2.17	-51.70	-30.04	38.26	147.33
CMCC 1 lumped 96 585	-35.83	3.38	-15.57	50.68	-24.71	4.46	-43.75	-27.64	54.18	142.62
CMCC 2 semi 86 585	-42.45	-10.50	-15.78	52.30	-29.71	-4.71	-57.43	-31.64	36.87	181.58
CMCC 2 semi 91 585	-40.90	-5.77	-15.30	57.23	-27.00	-3.18	-54.57	-28.65	42.10	165.91
CMCC 2 semi 96 585	-35.86	8.12	-15.22	59.90	-24.18	5.83	-44.98	-26.20	65.10	165.80
CMCC 3 snow 96 585	-34.29	7.29	-14.91	52.86	-22.00	10.05	-41.10	-24.06	58.12	153.26
CMCC 3 snow 01 585	-37.24	9.28	-16.14	53.70	-26.65	7.80	-43.77	-28.33	56.27	160.59
CMCC 4 distributed 86 585	-43.84	-12.23	-12.27	58.01	-24.28	-0.26	-55.31	-31.44	36.08	199.55
CMCC 4 distributed 91 585	-45.44	-7.76	-14.39	61.79	-22.30	4.03	-52.95	-36.11	39.16	173.11
CMCC 4 distributed 96 585	-39.17	12.67	-18.19	56.46	-22.64	6.55	-43.75	-30.84	63.48	154.41
EC 1 lumped 86 585	-73.92	-58.96	-64.38	-36.01	-66.17	-54.82	-79.94	-70.39	-32.34	20.95
EC 1 lumped 91 585	-72.85	-58.50	-64.39	-33.07	-64.73	-52.98	-79.07	-69.52	-29.50	18.13
EC 1 lumped 96 585	-69.87	-52.38	-63.65	-31.08	-62.31	-47.84	-75.43	-67.60	-19.92	19.40
EC 2 semi 86 585	-73.62	-59.52	-65.01	-33.00	-66.69	-55.00	-81.84	-70.48	-30.32	34.54
EC 2 semi 91 585	-72.58	-56.91	-64.15	-29.35	-64.90	-53.06	-80.40	-68.85	-26.60	28.19
EC 2 semi 96 585	-70.09	-50.37	-63.84	-27.20	-62.21	-47.28	-76.25	-67.09	-13.59	31.16
EC 3 snow 96 585	-68.81	-50.46	-62.92	-29.83	-60.58	-44.78	-74.07	-65.71	-17.53	24.78
EC 3 snow 01 585	-70.34	-49.66	-63.00	-29.55	-63.24	-46.22	-75.39	-67.62	-17.95	28.51
EC 4 distributed 86 585	-75.03	-61.15	-64.43	-33.09	-64.96	-54.02	-81.40	-71.59	-31.98	40.77
EC 4 distributed 91 585	-74.84	-57.98	-64.48	-29.59	-62.78	-54.65	-79.97	-72.90	-30.17	31.82
EC 4 distributed 96 585	-71.18	-47.41	-65.50	-28.31	-61.33	-46.52	-75.49	-69.36	-15.23	25.09
GFDL 1 lumped 86 585	-68.93	-53.45	-63.39	-33.22	-66.79	-53.66	-78.21	-70.76	-30.75	26.18
GFDL 1 lumped 91 585	-68.32	-52.80	-63.42	-32.43	-66.02	-52.90	-77.63	-69.97	-28.73	24.10
GFDL 1 lumped 96 585	-67.37	-49.15	-64.16	-34.57	-65.84	-50.78	-75.00	-69.42	-23.78	18.89
GFDL 2 semi 86 585	-67.53	-52.52	-63.10	-28.42	-66.30	-52.64	-79.21	-70.04	-26.76	45.19
GFDL 2 semi 91 585	-67.26	-50.25	-63.21	-27.64	-65.47	-52.02	-78.10	-69.17	-24.62	37.21
GFDL 2 semi 96 585	-66.79	-45.81	-64.14	-30.33	-65.19	-49.26	-75.18	-68.77	-17.14	32.67
GFDL 3 snow 96 585	-66.59	-47.35	-64.09	-34.02	-64.70	-48.17	-74.00	-67.96	-22.32	24.04
GFDL 3 snow 01 585	-66.53	-45.17	-64.57	-31.87	-65.90	-47.93	-74.36	-69.23	-20.84	30.35
GFDL 4 distributed 86 585	-69.61	-55.22	-61.53	-28.21	-64.26	-51.46	-79.20	-70.81	-28.68	54.94
GFDL 4 distributed 91 585	-70.61	-52.96	-60.76	-25.84	-63.42	-52.70	-78.20	-72.22	-25.96	43.44
GFDL 4 distributed 96 585	-69.34	-45.19	-63.72	-31.78	-63.72	-48.66	-75.20	-70.39	-17.64	31.25
MPI 1 lumped 86 585	-81.30	-73.29	-75.98	-56.58	-78.23	-69.64	-86.82	-80.43	-54.58	-19.11
MPI 1 lumped 91 585	-80.79	-73.13	-76.01	-55.45	-77.56	-68.78	-86.47	-79.91	-53.17	-20.30

Continued on next page

Tab. 6.54: Changes in discharge for annual runoff for mean over 30 years (3/3) [%] (Continuation)

Variant	21	22	23	24	25	26	27	28	29	30
MPI 1 lumped 96 585	-79.84	-70.42	-76.26	-56.14	-77.10	-67.01	-84.68	-79.40	-49.24	-22.65
MPI 2 semi 86 585	-80.64	-73.31	-75.88	-53.64	-78.06	-69.19	-87.74	-80.05	-52.26	-7.96
MPI 2 semi 91 585	-80.29	-71.96	-75.75	-52.38	-77.36	-68.46	-87.06	-79.26	-50.55	-12.83
MPI 2 semi 96 585	-79.63	-68.96	-76.22	-53.17	-76.76	-66.25	-85.00	-78.87	-44.77	-14.61
MPI 3 snow 96 585	-79.40	-69.43	-75.98	-55.70	-76.29	-65.31	-84.01	-78.33	-48.09	-19.60
MPI 3 snow 01 585	-79.84	-68.56	-76.26	-54.69	-77.40	-65.60	-84.58	-79.30	-47.59	-16.35
MPI 4 distributed 86 585	-81.50	-74.42	-75.34	-53.03	-76.64	-68.29	-87.40	-80.66	-53.12	-1.25
MPI 4 distributed 91 585	-81.96	-72.78	-75.40	-51.48	-76.00	-69.07	-86.73	-81.68	-51.74	-8.55
MPI 4 distributed 96 585	-80.78	-67.62	-76.69	-53.84	-76.02	-65.88	-84.64	-80.22	-45.30	-15.95
MRI 1 lumped 86 585	-88.24	-81.61	-83.86	-72.30	-85.72	-80.67	-91.12	-87.31	-72.34	-46.92
MRI 1 lumped 91 585	-87.94	-81.47	-83.94	-71.59	-85.34	-80.21	-90.85	-86.99	-71.62	-48.53
MRI 1 lumped 96 585	-87.00	-79.27	-83.86	-71.55	-84.78	-78.68	-89.45	-86.45	-68.44	-49.25
MRI 2 semi 86 585	-88.02	-81.71	-83.98	-70.77	-85.82	-80.60	-91.85	-87.23	-71.46	-40.12
MRI 2 semi 91 585	-87.74	-80.67	-83.80	-69.80	-85.31	-80.10	-91.32	-86.67	-70.39	-43.45
MRI 2 semi 96 585	-86.98	-78.23	-83.93	-69.81	-84.68	-78.28	-89.70	-86.23	-65.95	-43.77
MRI 3 snow 96 585	-86.65	-78.49	-83.62	-71.20	-84.20	-77.48	-88.92	-85.73	-67.60	-47.01
MRI 3 snow 01 585	-87.07	-77.85	-83.81	-70.69	-85.07	-77.77	-89.31	-86.47	-67.44	-44.72
MRI 4 distributed 86 585	-88.62	-82.64	-83.43	-70.41	-84.96	-79.94	-91.71	-87.60	-72.23	-37.58
MRI 4 distributed 91 585	-88.74	-81.51	-83.57	-69.33	-84.31	-80.53	-91.13	-88.29	-71.40	-41.87
MRI 4 distributed 96 585	-87.61	-77.47	-84.46	-70.19	-84.20	-77.90	-89.43	-87.18	-66.38	-45.95
TAI 1 lumped 86 585	-86.05	-79.66	-82.33	-68.08	-83.98	-78.44	-90.53	-85.43	-67.82	-42.22
TAI 1 lumped 91 585	-85.39	-79.05	-82.29	-67.08	-83.39	-77.73	-90.05	-84.85	-66.55	-43.08
TAI 1 lumped 96 585	-84.48	-76.73	-82.46	-67.73	-83.04	-76.56	-88.42	-84.37	-63.80	-44.71
TAI 2 semi 86 585	-85.36	-79.29	-82.16	-65.57	-83.67	-77.82	-90.93	-84.96	-65.98	-33.76
TAI 2 semi 91 585	-84.95	-77.99	-82.11	-64.71	-83.16	-77.35	-90.22	-84.33	-64.76	-37.40
TAI 2 semi 96 585	-84.12	-75.15	-82.35	-65.31	-82.62	-75.72	-88.29	-83.85	-60.48	-38.36
TAI 3 snow 96 585	-84.08	-75.79	-82.38	-67.40	-82.42	-75.37	-87.83	-83.61	-62.99	-42.30
TAI 3 snow 01 585	-84.53	-75.04	-82.61	-66.75	-83.25	-75.66	-88.19	-84.33	-62.82	-40.13
TAI 4 distributed 86 585	-85.86	-80.12	-81.18	-65.19	-82.56	-77.17	-90.75	-85.19	-66.38	-29.91
TAI 4 distributed 91 585	-86.45	-79.48	-81.14	-63.97	-82.09	-77.77	-90.44	-85.80	-65.59	-35.37
TAI 4 distributed 96 585	-85.43	-75.04	-82.69	-66.26	-82.25	-75.75	-88.52	-84.97	-61.33	-40.67

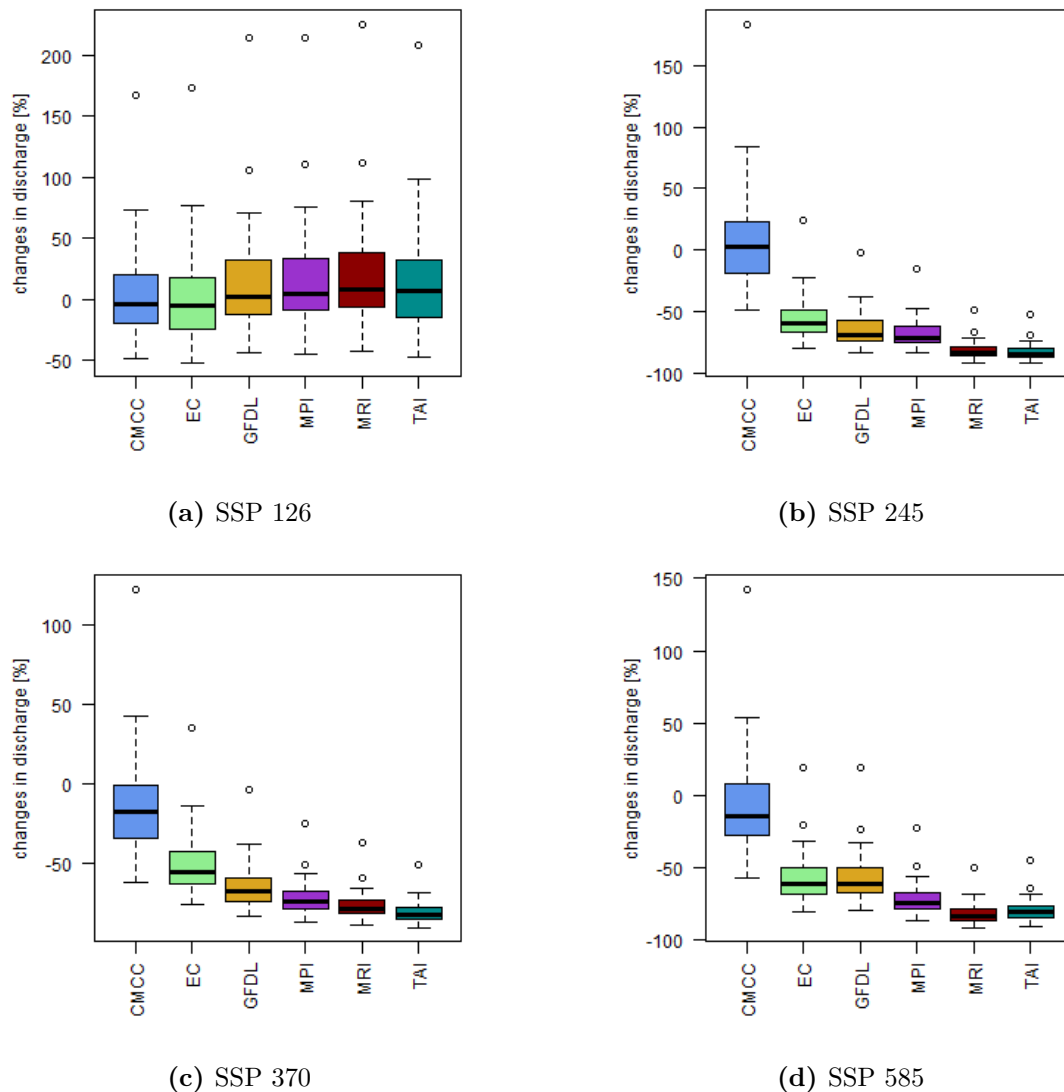


Fig. 6.36: Distribution of changes for annual mean discharges over 30 years compared to historical period for calibration variant lumped in period 1996-2005. Panel (a) shows sustainable and green shared socioeconomic pathways (SSP126), (b) the medium pathway (SSP245), (c) regional rivalry (SSP370) and (d) fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins is 47.

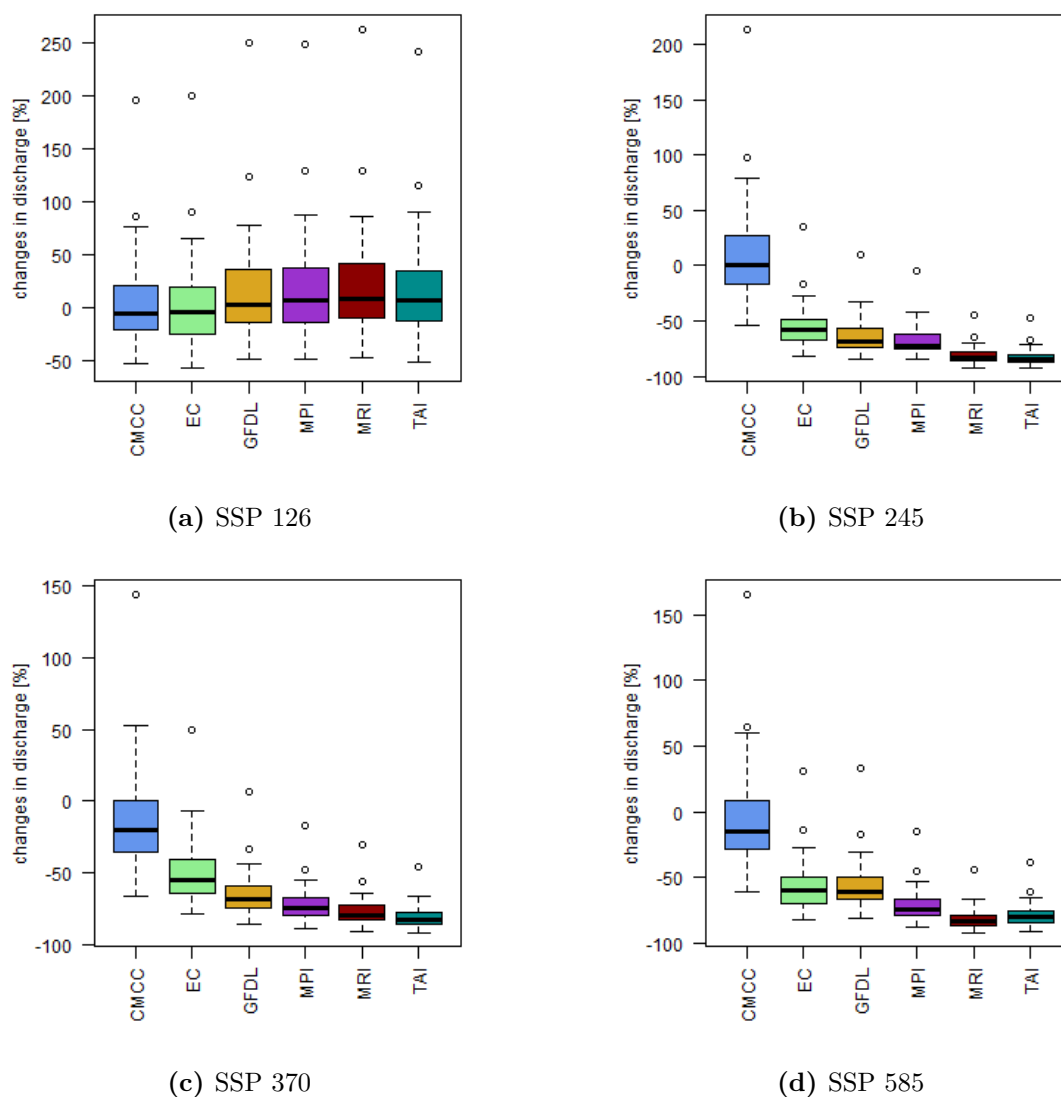


Fig. 6.37: Distribution of changes for annual mean discharges over 30 years compared to historical period for calibration variant semi-distributed in period 1996-2005. Panel (a) shows sustainable and green shared socioeconomic pathways (SSP126), (b) the medium pathway (SSP245), (c) regional rivalry (SSP370) and (d) fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins is 38.

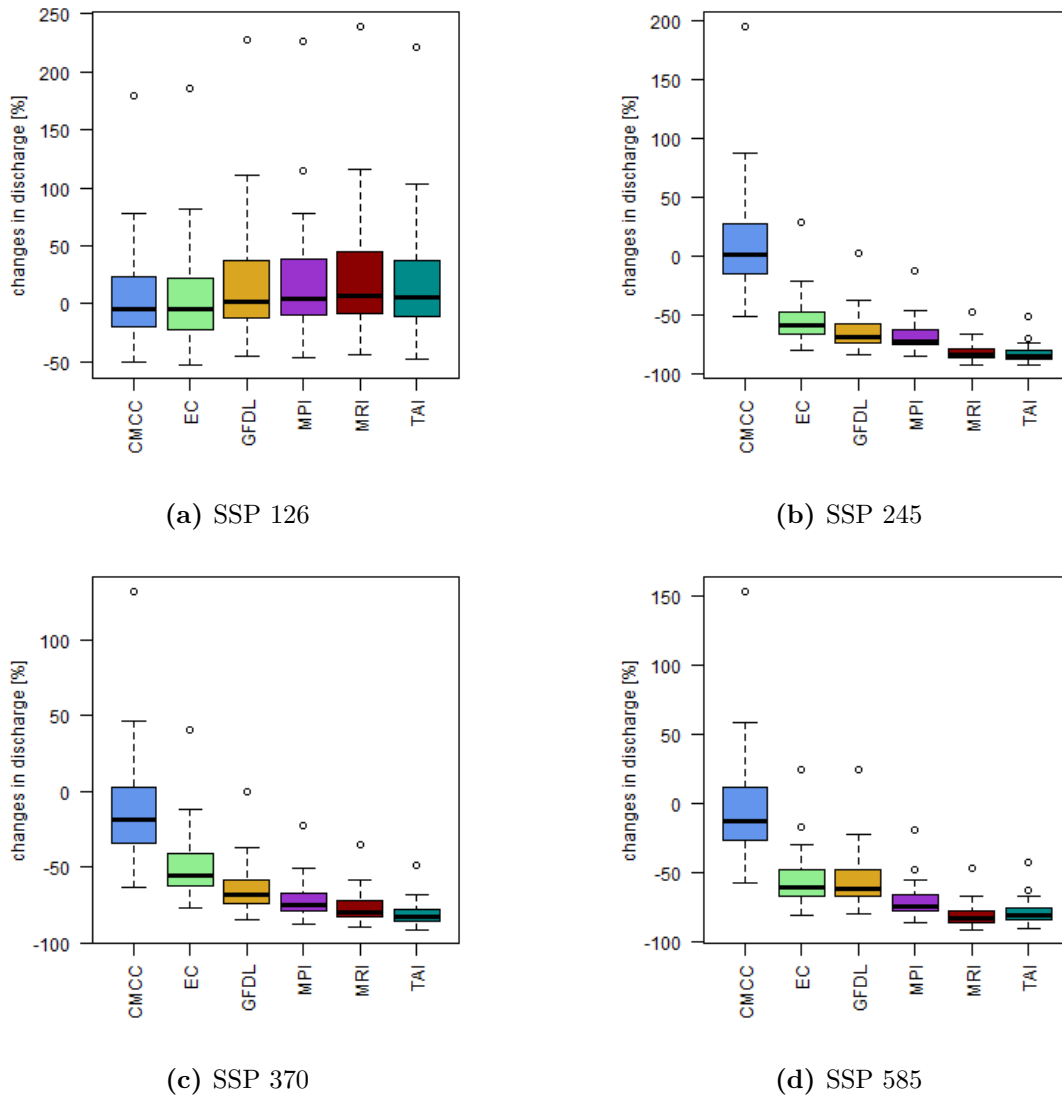


Fig. 6.38: Distribution of changes for annual mean discharges over 30 years compared to historical period for calibration variant snow in period 1996–2005. Panel (a) shows sustainable and green shared socioeconomic pathways (SSP126), (b) the medium pathway (SSP245), (c) regional rivalry (SSP370) and (d) fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins is 47.

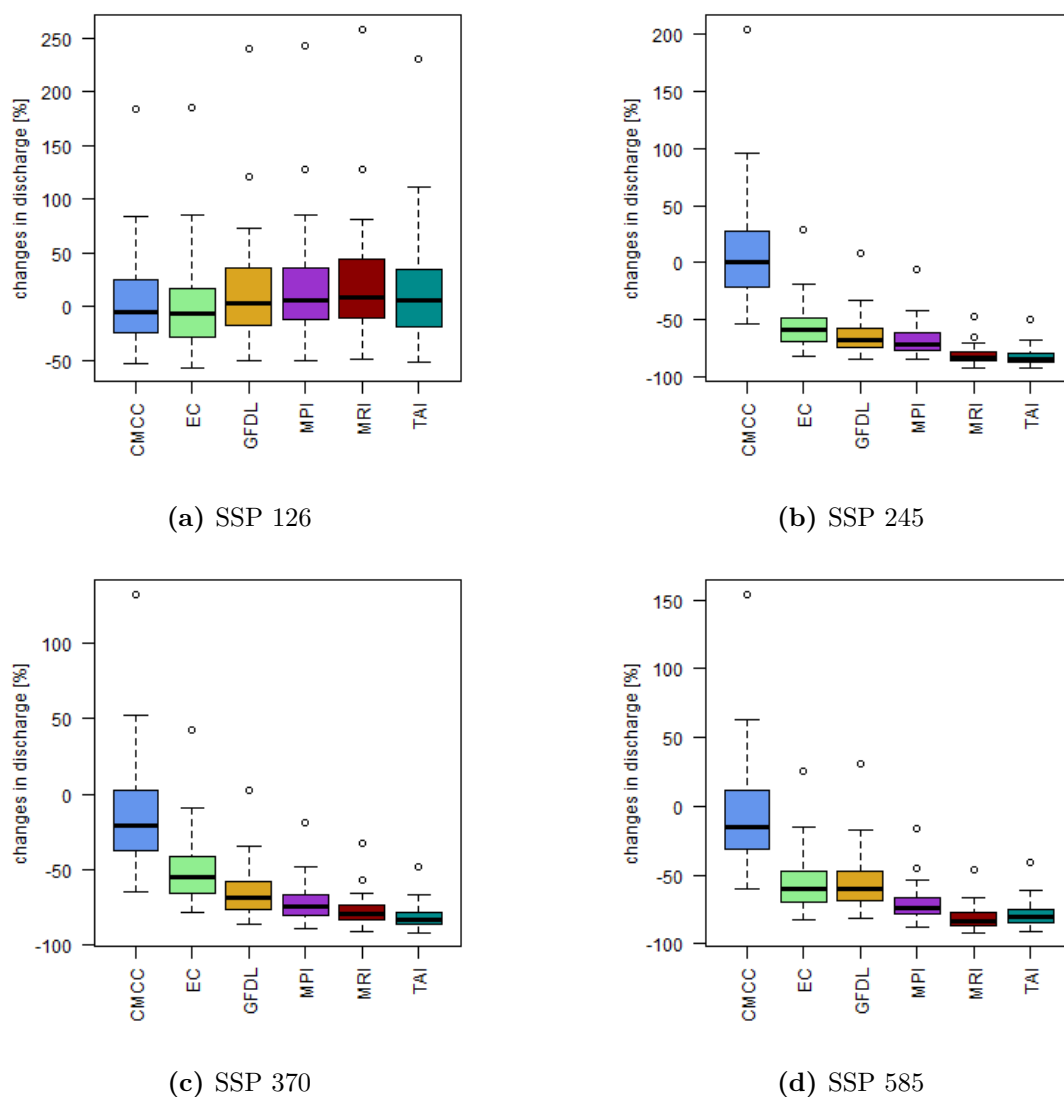


Fig. 6.39: Distribution of changes for annual mean discharges over 30 years compared to historical period for calibration variant distributed in period 1996-2005. Panel (a) shows sustainable and green shared socioeconomic pathways (SSP126), (b) the medium pathway (SSP245), (c) regional rivalry (SSP370) and (d) fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins is 21.

6.4 Uncertainty of hydrological projections

6.4.1 Comparison of seasonal data

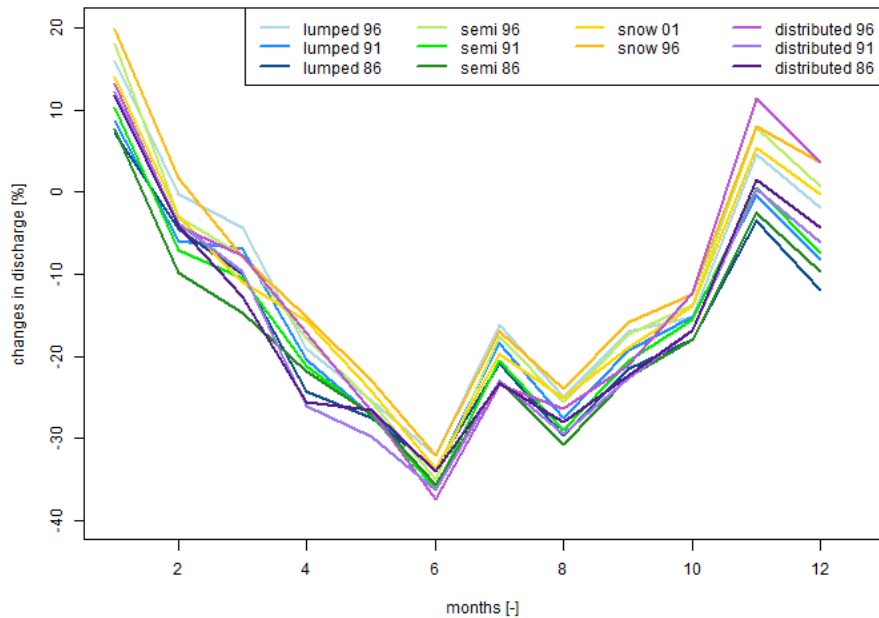


Fig. 6.40: Projections of seasonal runoff changes estimated from the CMCC climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

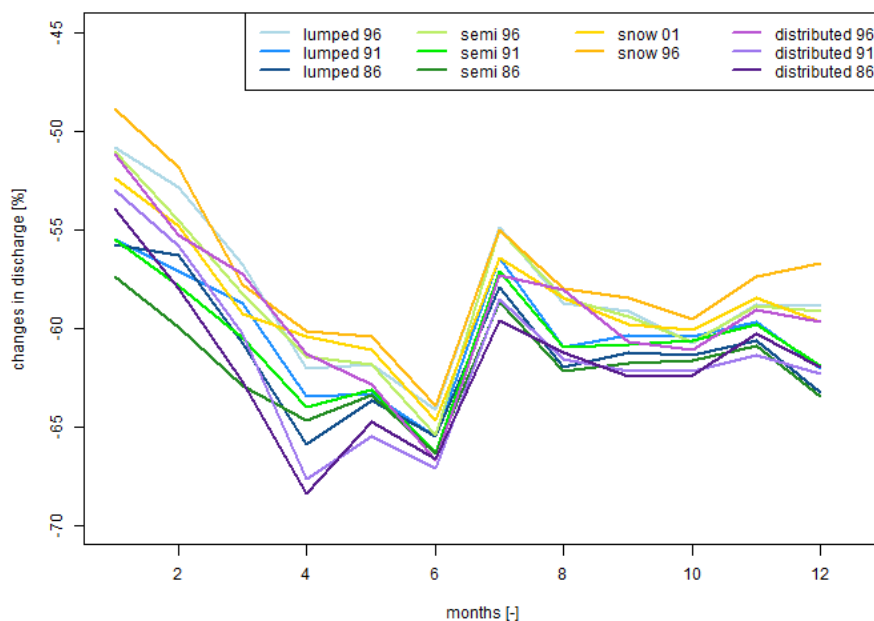


Fig. 6.41: Projections of seasonal runoff changes estimated from the EC climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

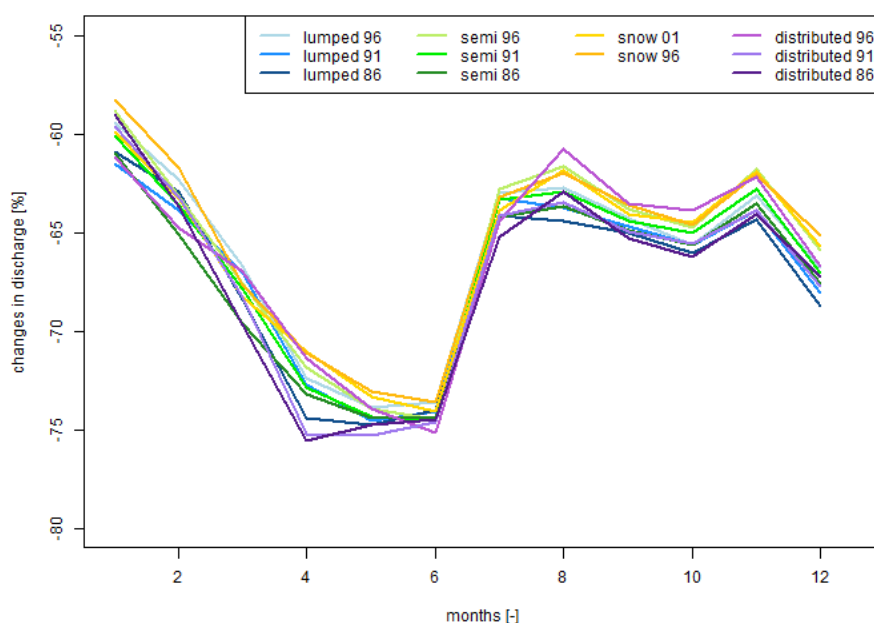


Fig. 6.42: Projections of seasonal runoff changes estimated from the GFDL climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

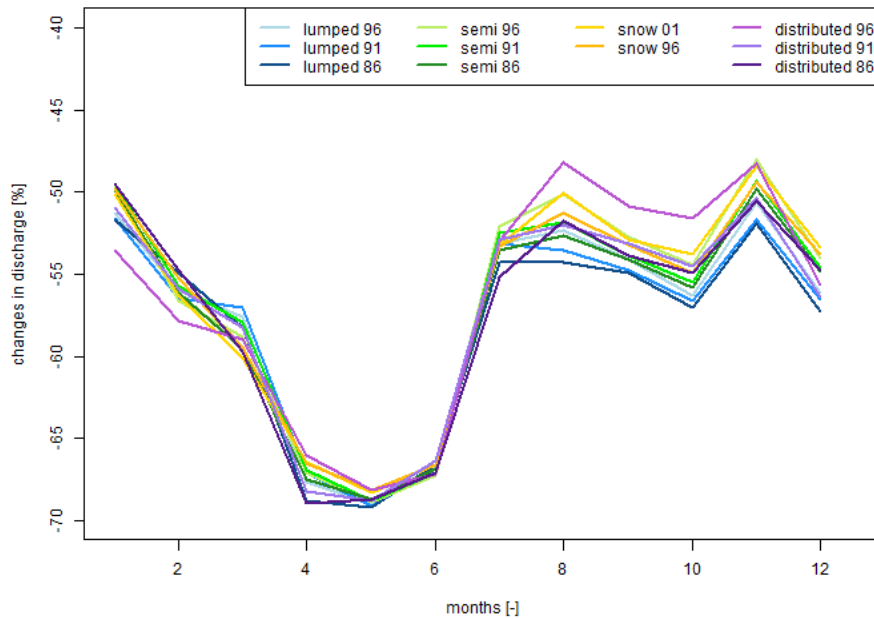


Fig. 6.43: Projections of seasonal runoff changes estimated from the GFDL climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

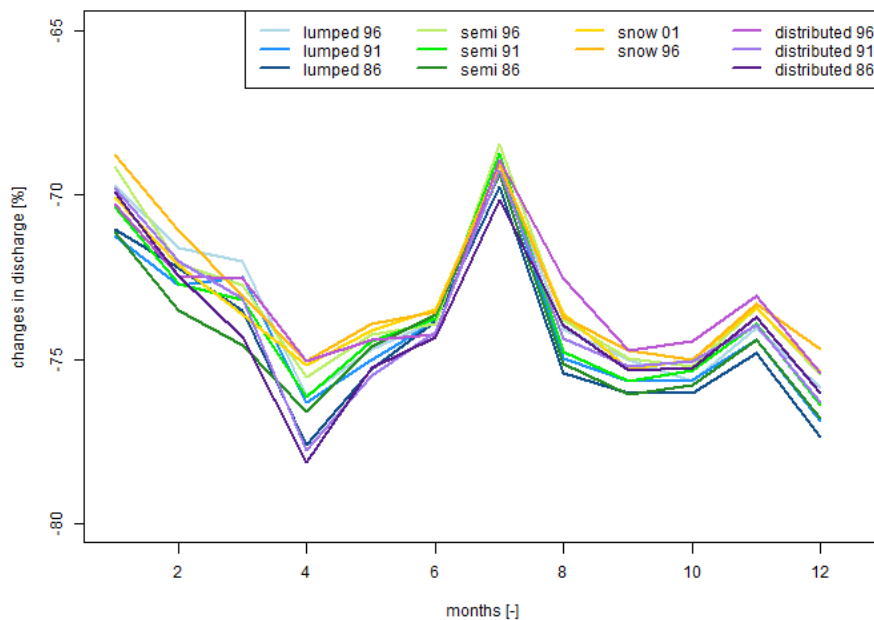


Fig. 6.44: Projections of seasonal runoff changes estimated from the MPI climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

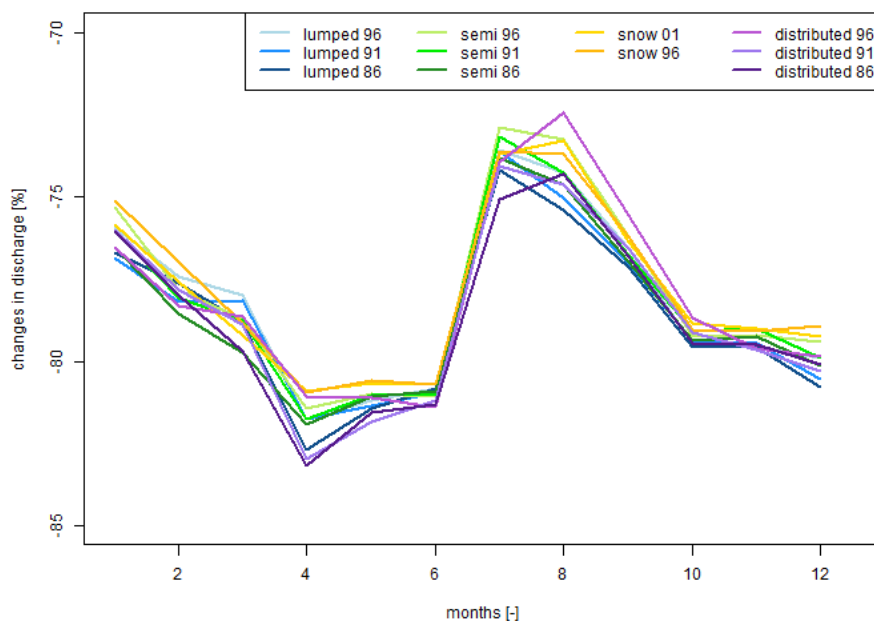


Fig. 6.45: Projections of seasonal runoff changes estimated from the MRI climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

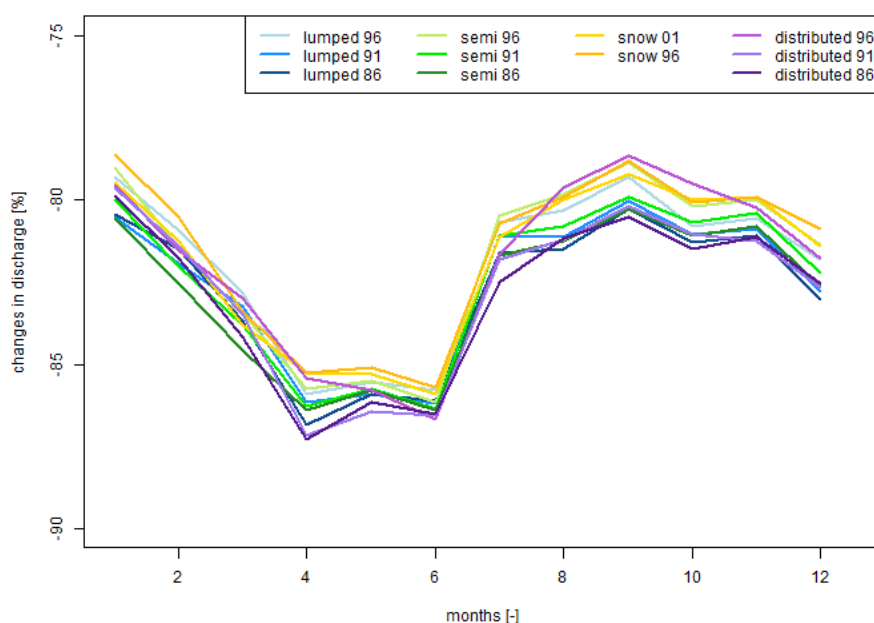


Fig. 6.46: Projections of seasonal runoff changes estimated from the MRI climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

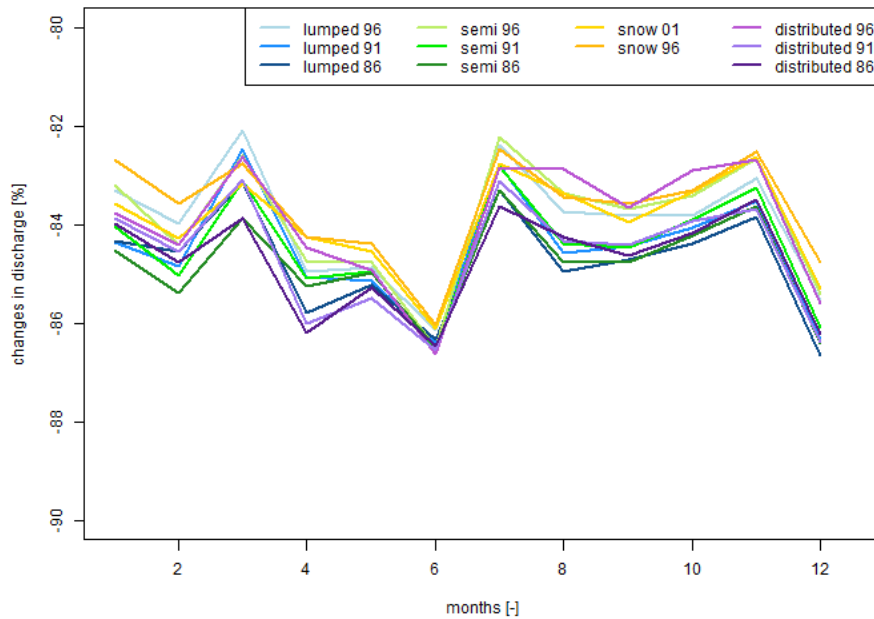


Fig. 6.47: Projections of seasonal runoff changes estimated from the TAI climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

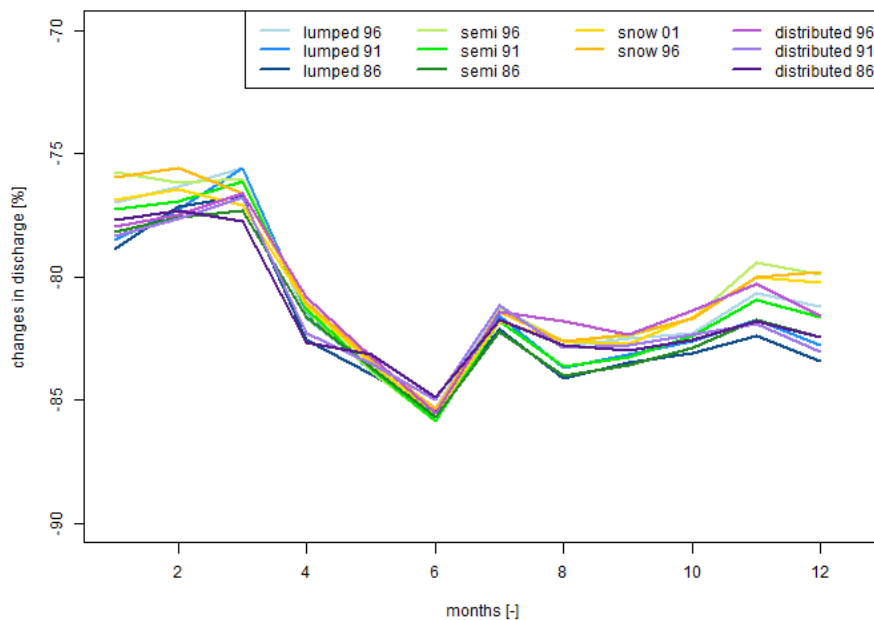


Fig. 6.48: Projections of seasonal runoff changes estimated from the TAI climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 30-year historical period for reference.

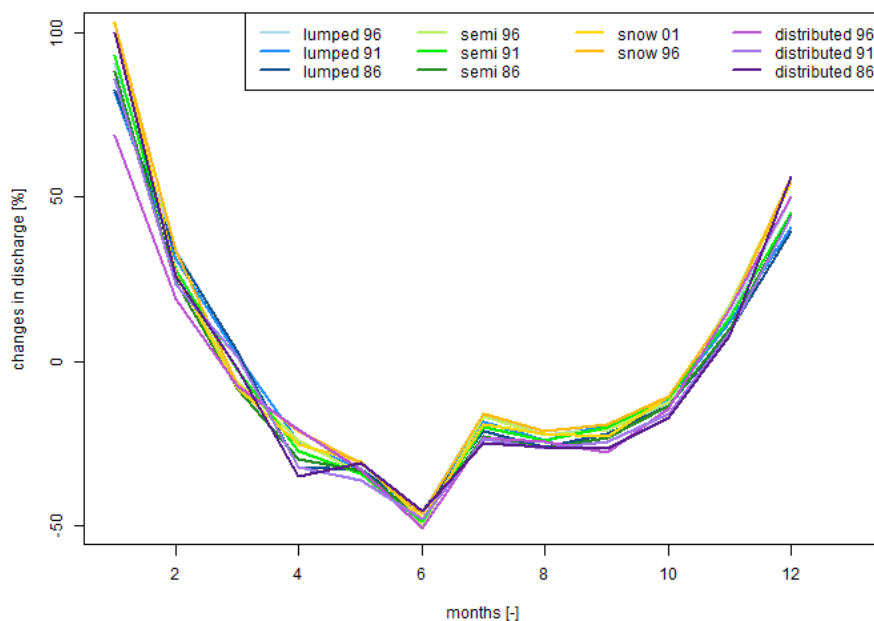


Fig. 6.49: Projections of seasonal runoff changes estimated from the CMCC climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

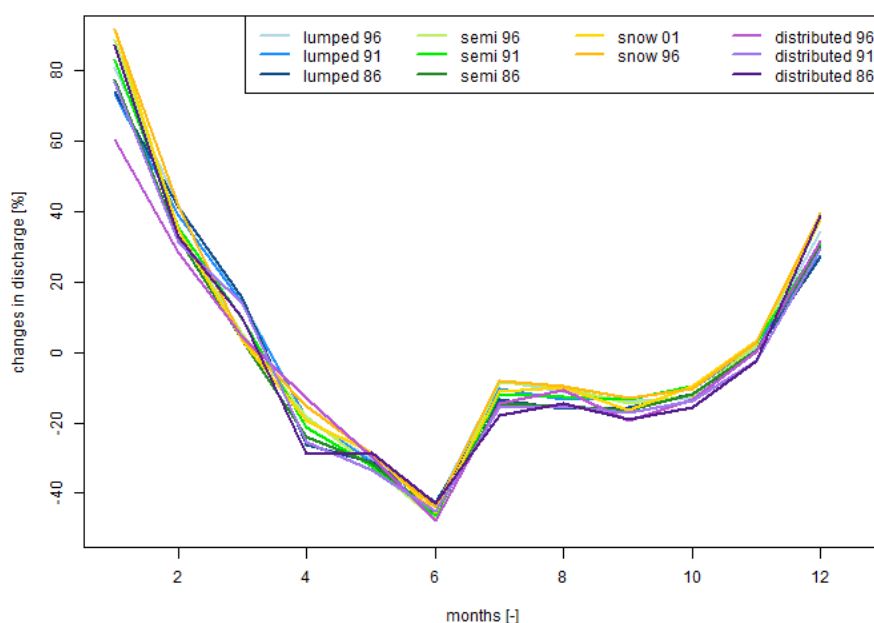


Fig. 6.50: Projections of seasonal runoff changes estimated from the CMCC climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

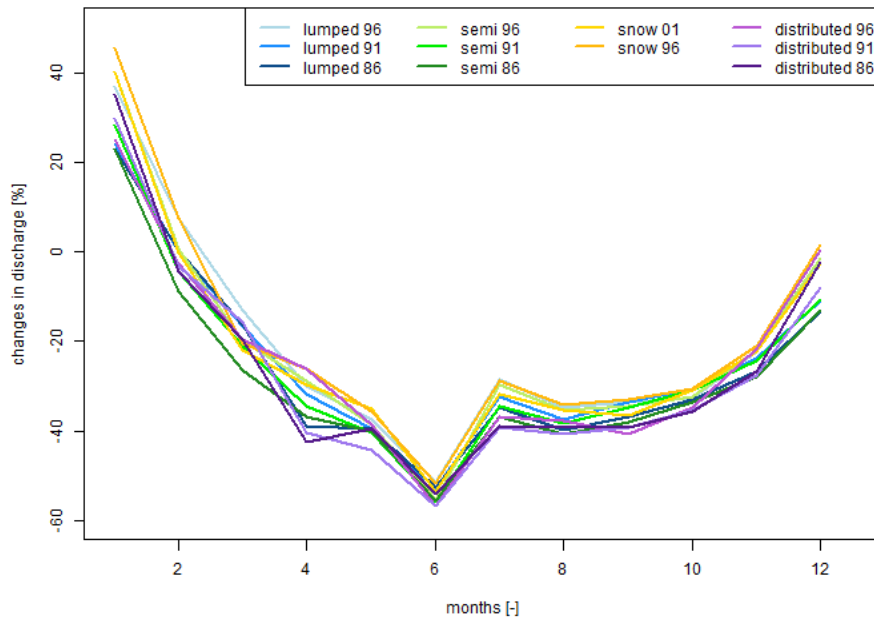


Fig. 6.51: Projections of seasonal runoff changes estimated from the CMCC climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

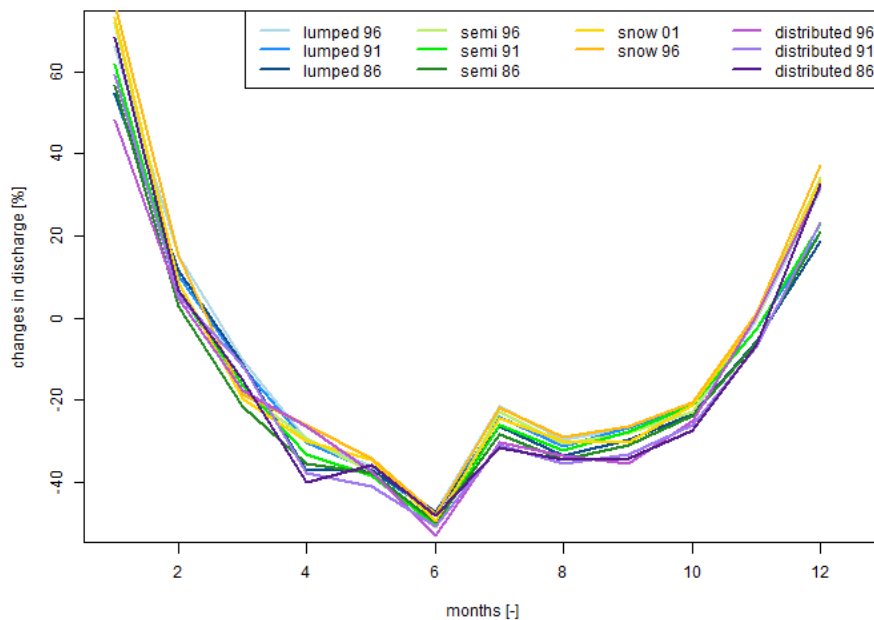


Fig. 6.52: Projections of seasonal runoff changes estimated from the CMCC climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

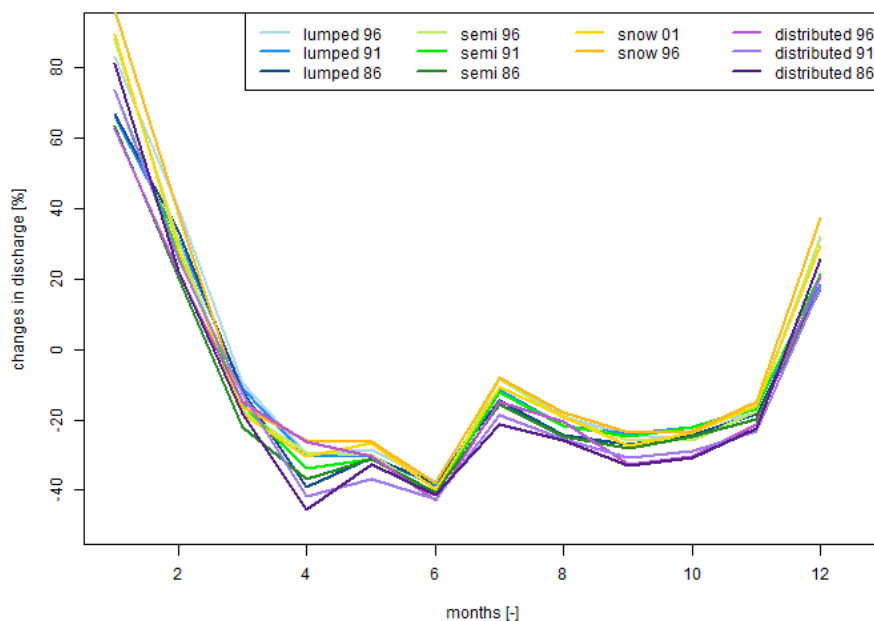


Fig. 6.53: Projections of seasonal runoff changes estimated from the EC climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

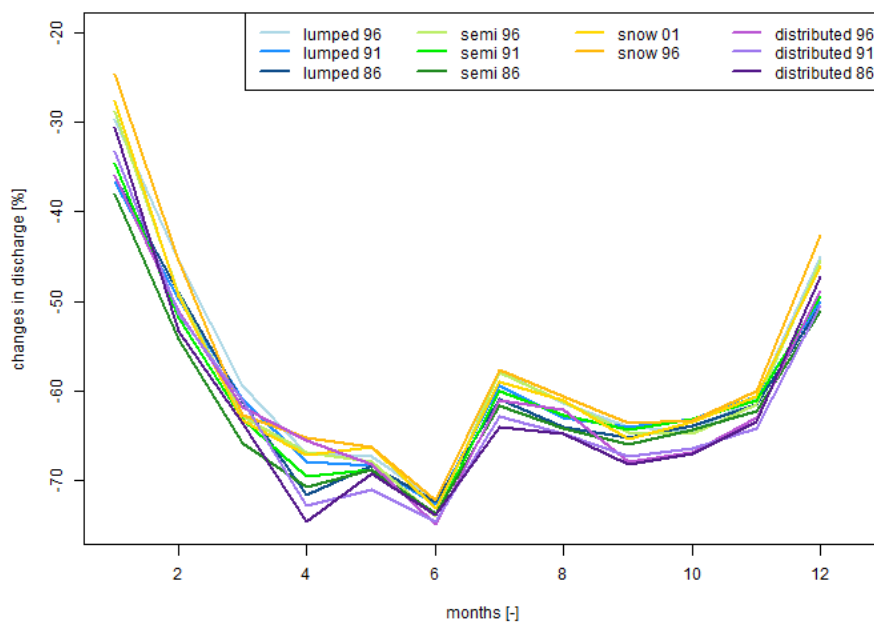


Fig. 6.54: Projections of seasonal runoff changes estimated from the EC climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

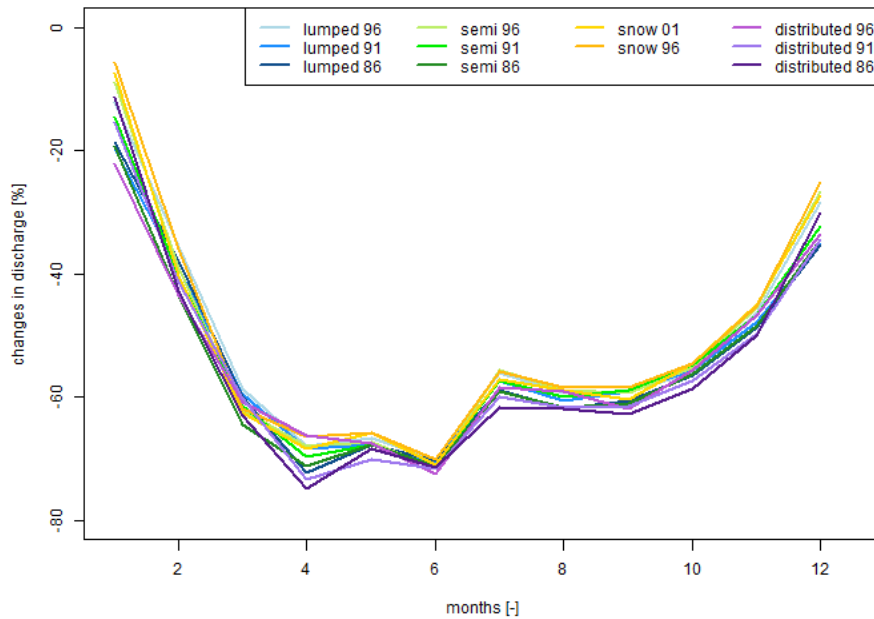


Fig. 6.55: Projections of seasonal runoff changes estimated from the EC climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

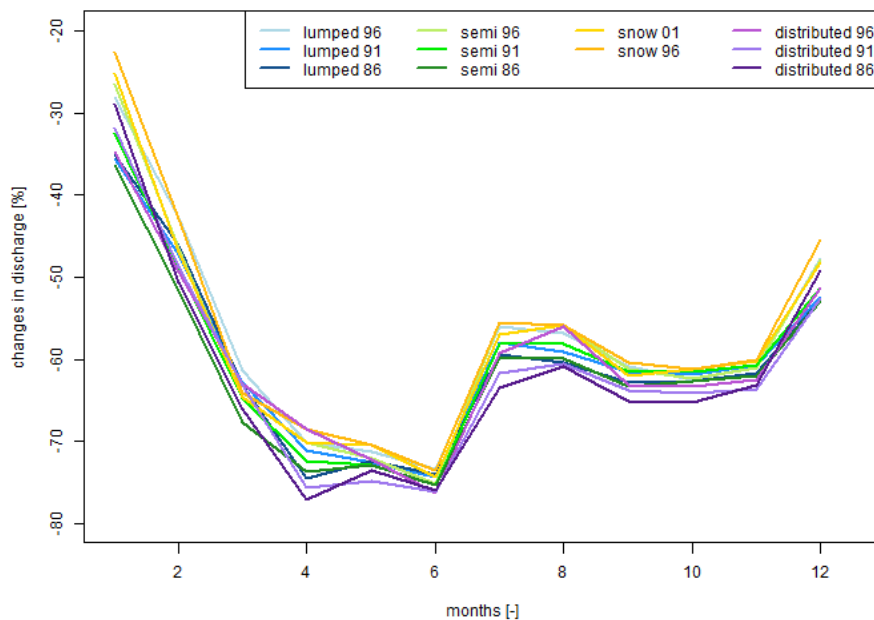


Fig. 6.56: Projections of seasonal runoff changes estimated from the EC climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

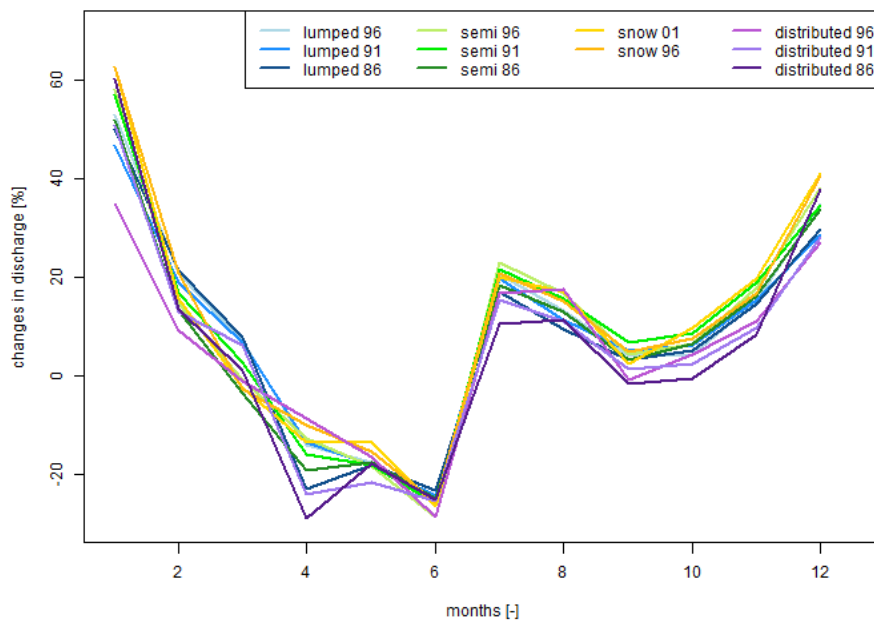


Fig. 6.57: Projections of seasonal runoff changes estimated from the GFDL climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

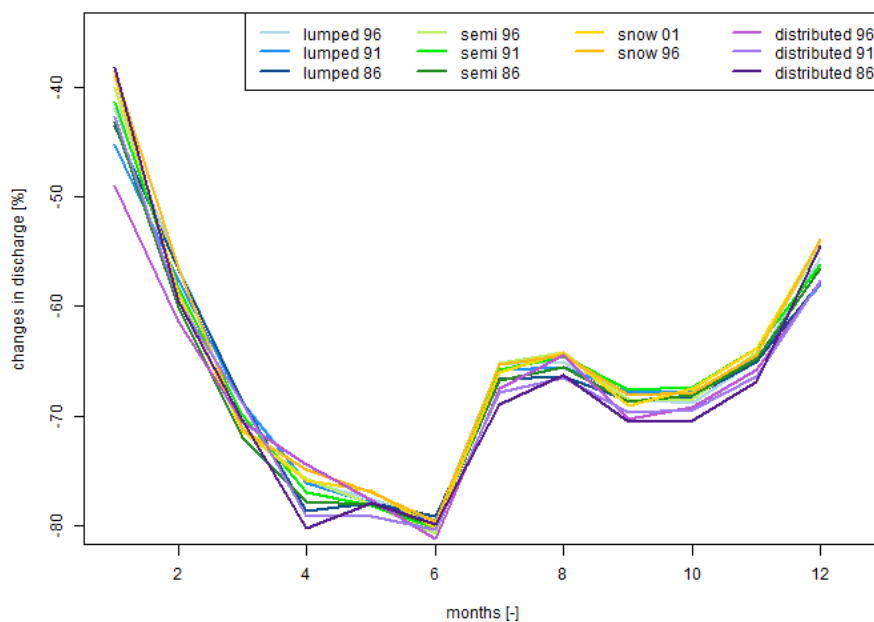


Fig. 6.58: Projections of seasonal runoff changes estimated from the GFDL climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

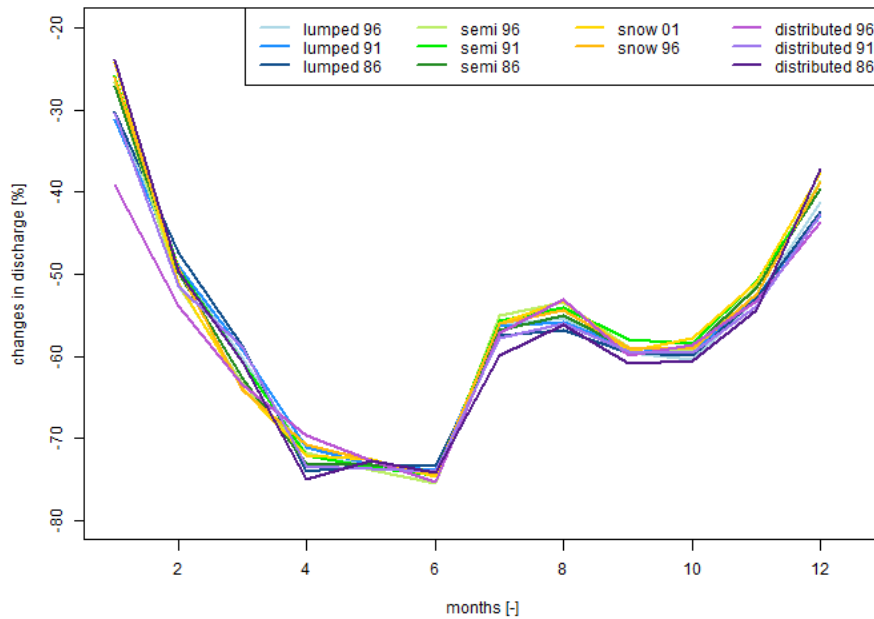


Fig. 6.59: Projections of seasonal runoff changes estimated from the GFDL climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

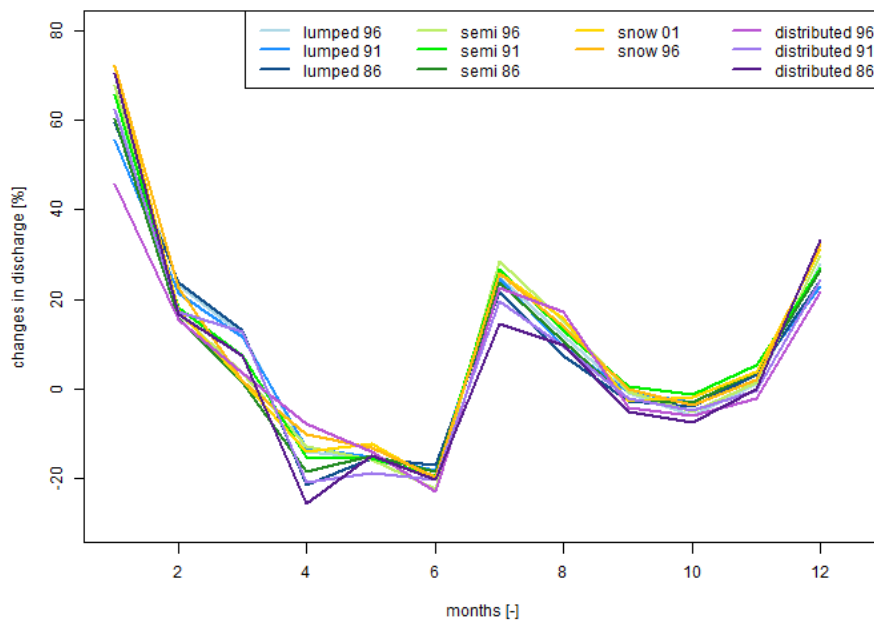


Fig. 6.60: Projections of seasonal runoff changes estimated from the MPI climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

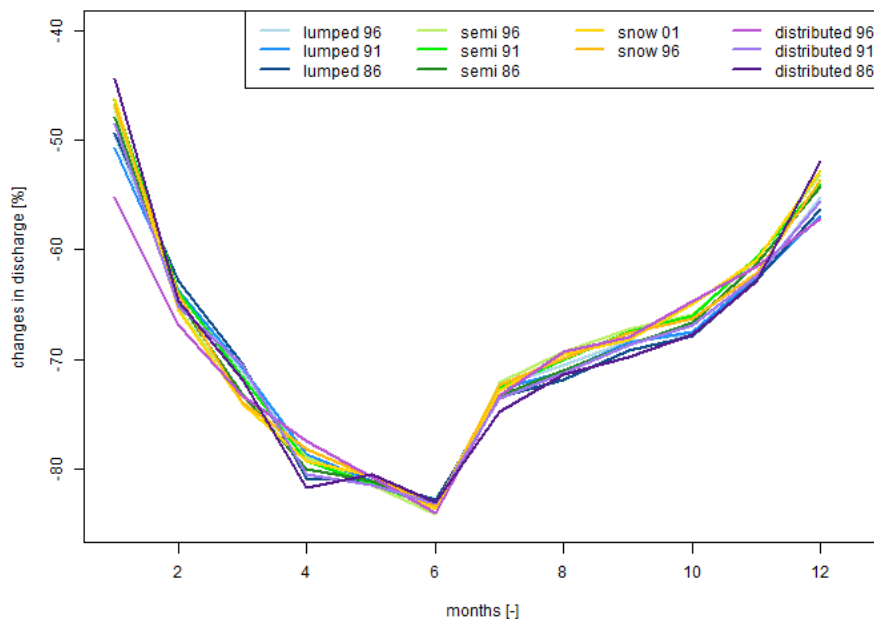


Fig. 6.61: Projections of seasonal runoff changes estimated from the MPI climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

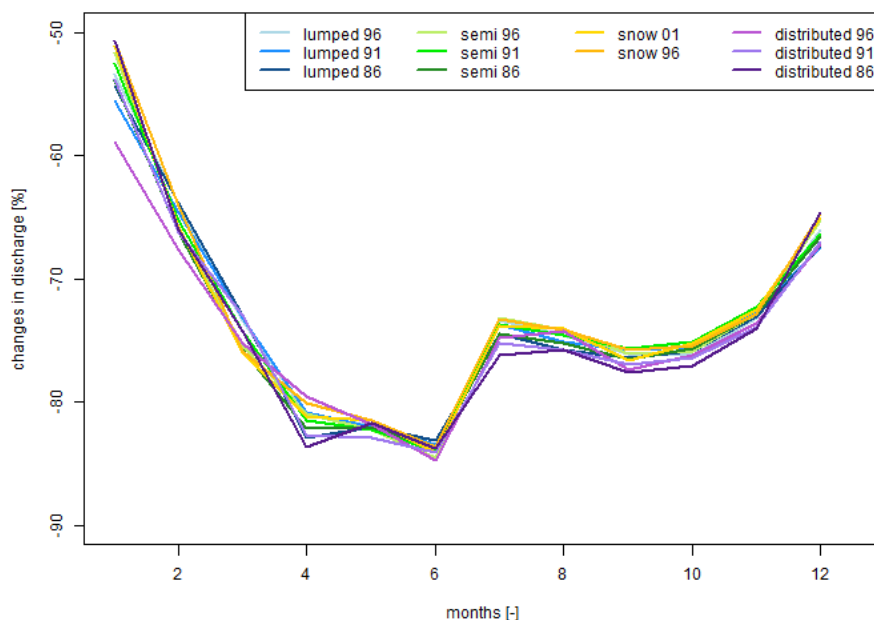


Fig. 6.62: Projections of seasonal runoff changes estimated from the MPI climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

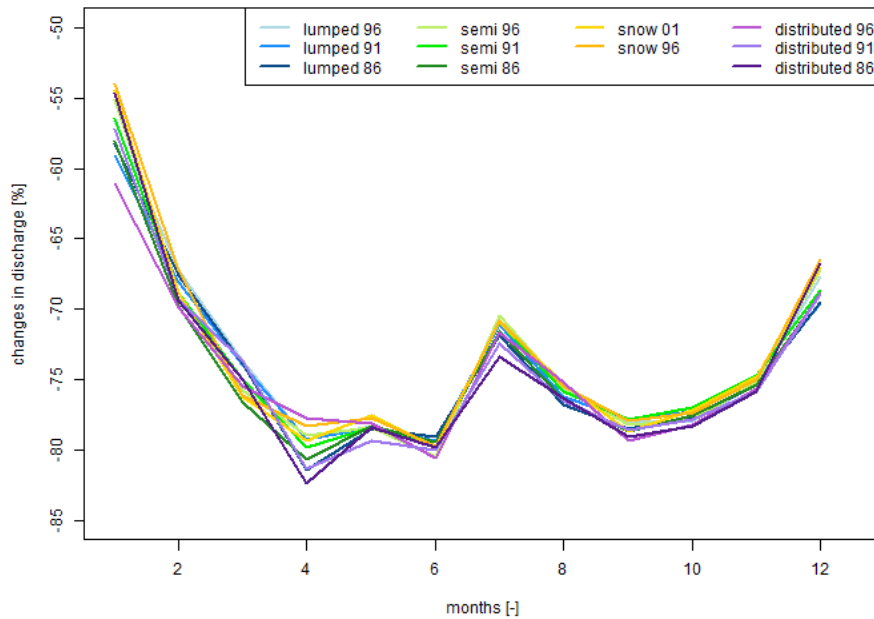


Fig. 6.63: Projections of seasonal runoff changes estimated from the MPI climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

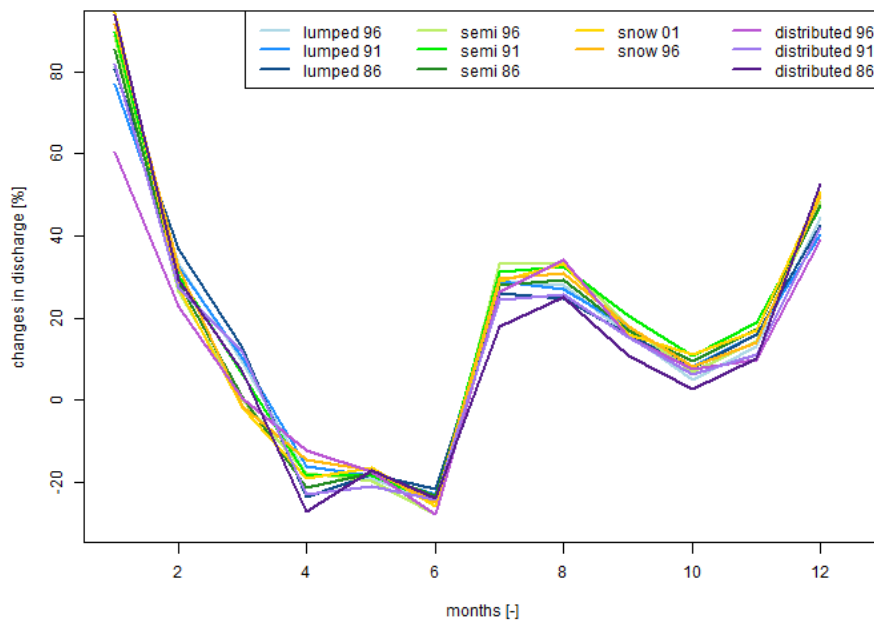


Fig. 6.64: Projections of seasonal runoff changes estimated from the MRI climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

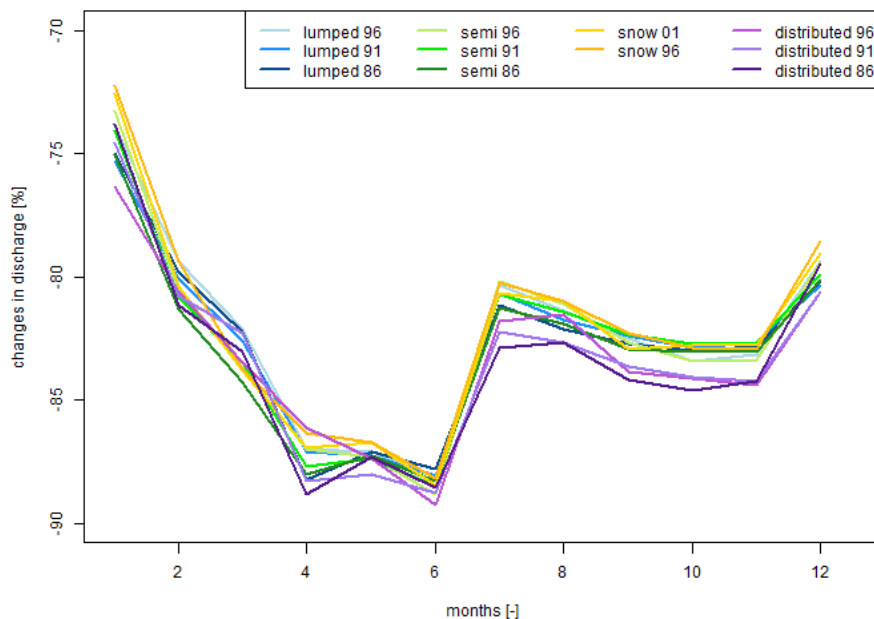


Fig. 6.65: Projections of seasonal runoff changes estimated from the MRI climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

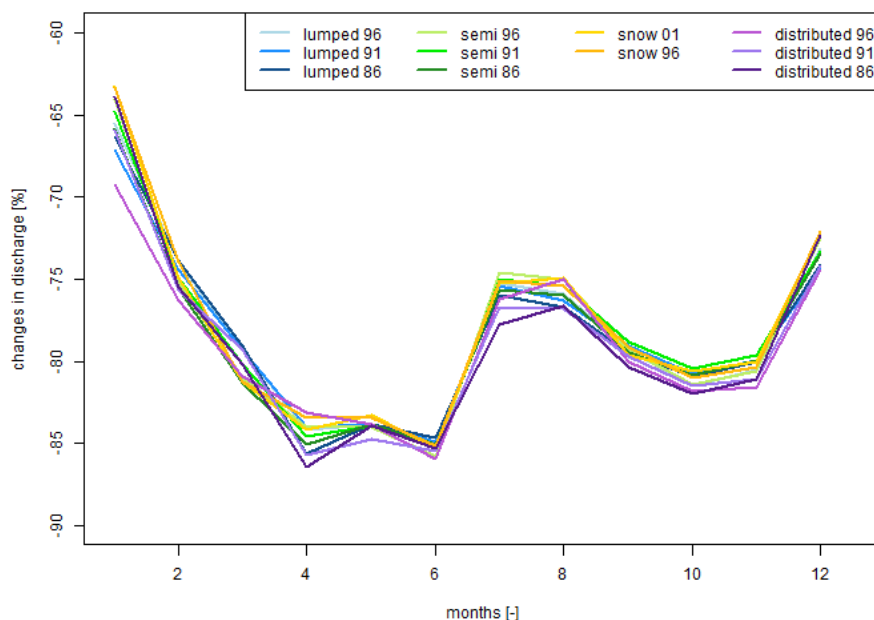


Fig. 6.66: Projections of seasonal runoff changes estimated from the MRI climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

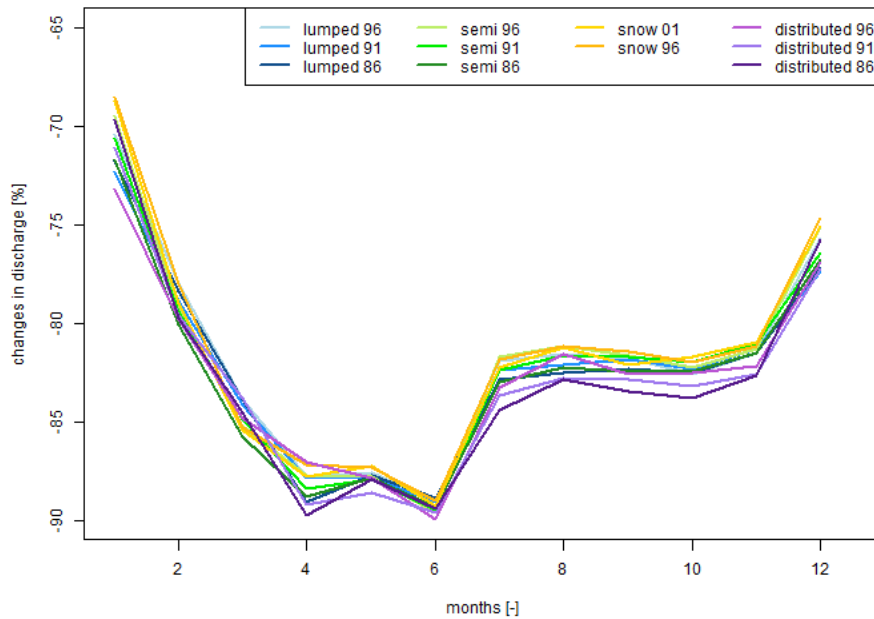


Fig. 6.67: Projections of seasonal runoff changes estimated from the MRI climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

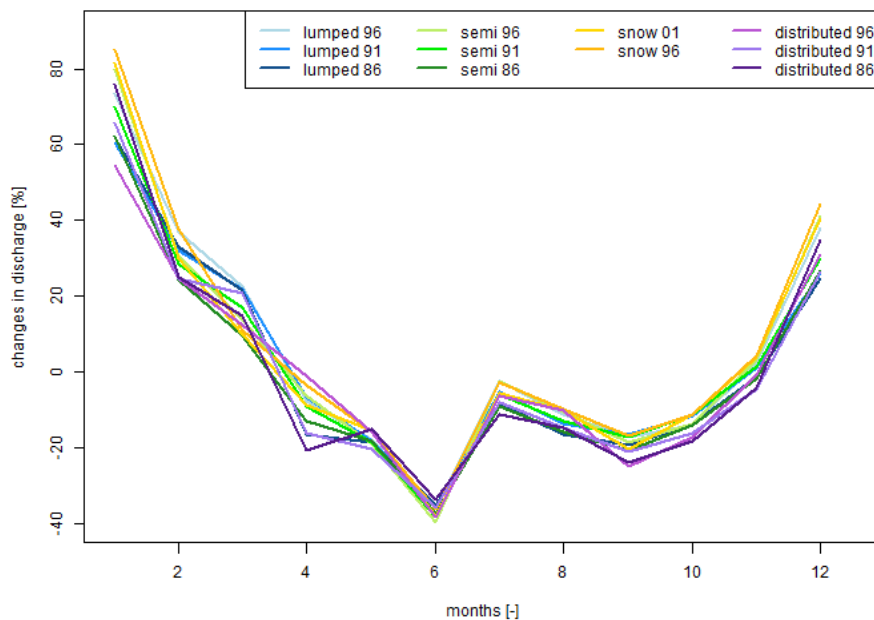


Fig. 6.68: Projections of seasonal runoff changes estimated from the TAI climate model representing sustainable and green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

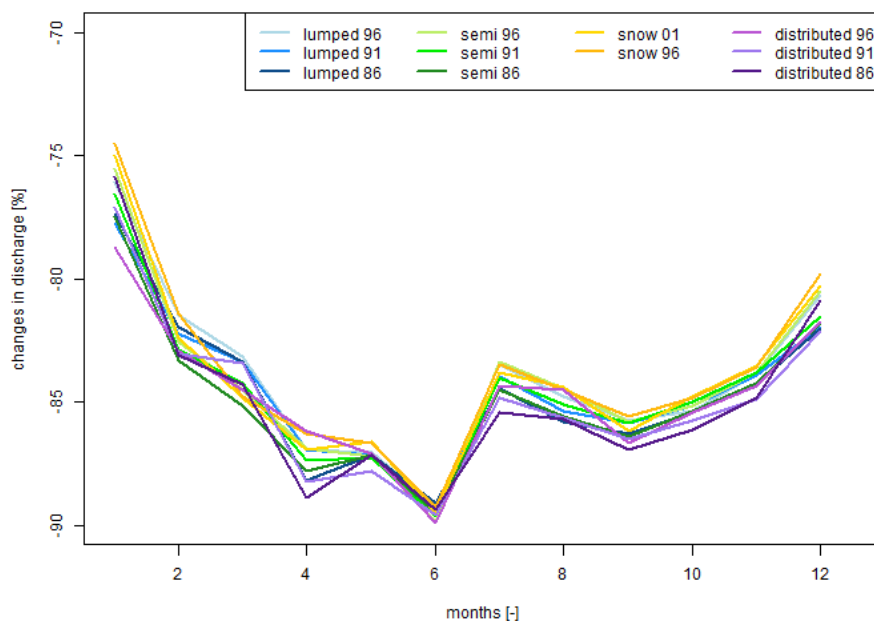


Fig. 6.69: Projections of seasonal runoff changes estimated from the TAI climate model representing the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

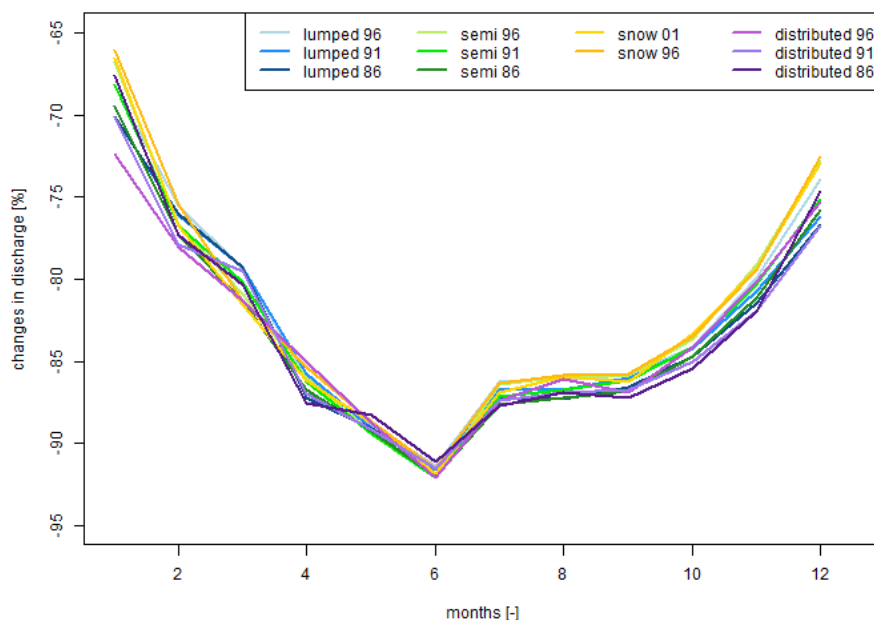


Fig. 6.70: Projections of seasonal runoff changes estimated from the TAI climate model representing regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

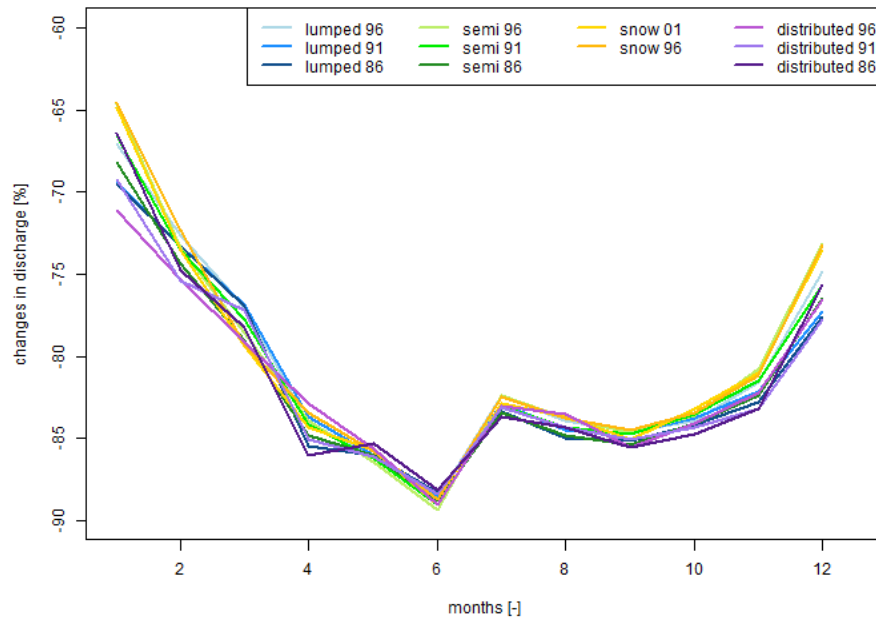
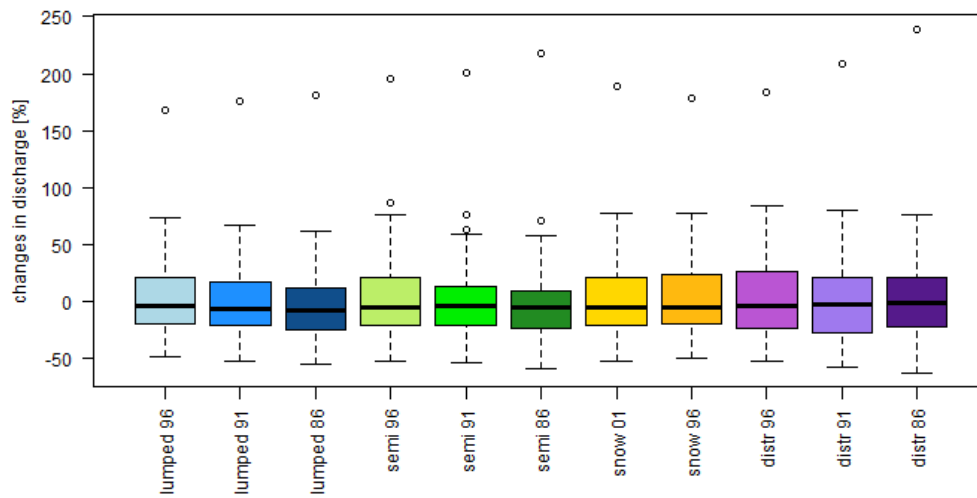


Fig. 6.71: Projections of seasonal runoff changes estimated from the TAI climate model representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by the different calibration variants labeled as lumped, semi, snow and distr for different calibration periods and a 10-year historical period for reference.

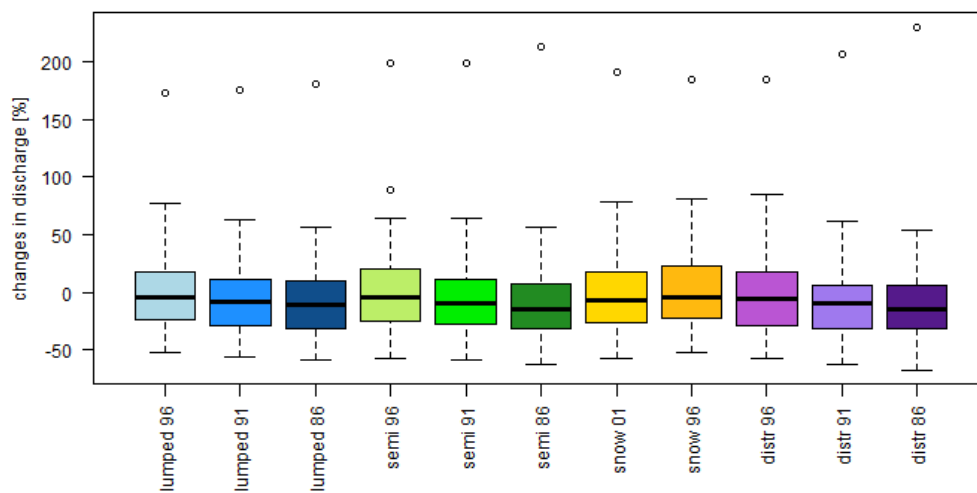
Die approbierte gedruckte Originalversion dieser Diplomarbeit ist an der TU Wien Bibliothek verfügbar
The approved original version of this thesis is available in print at TU Wien Bibliothek.



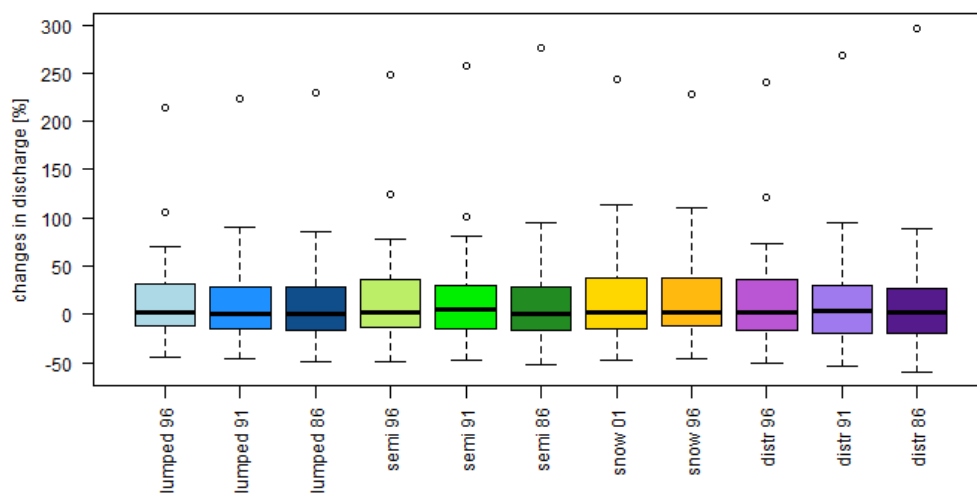
6.4.2 Comparison of annual data



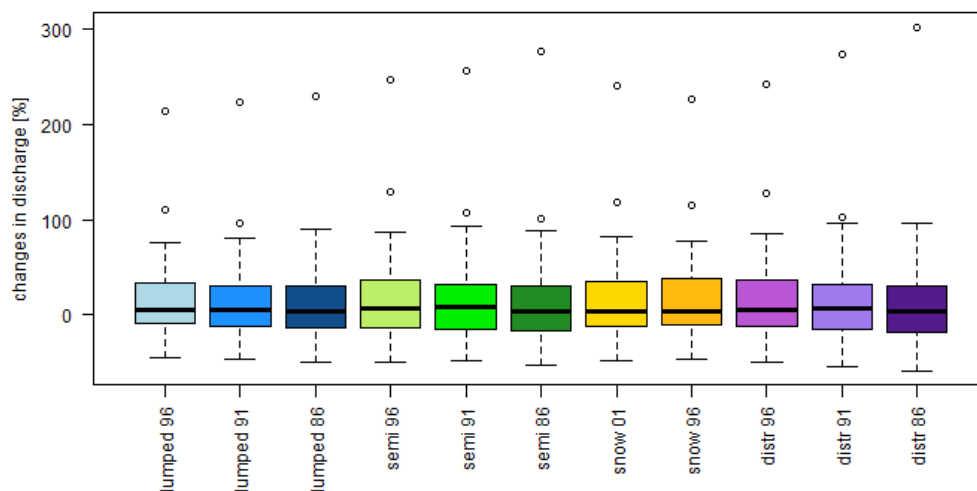
(a) CMCC



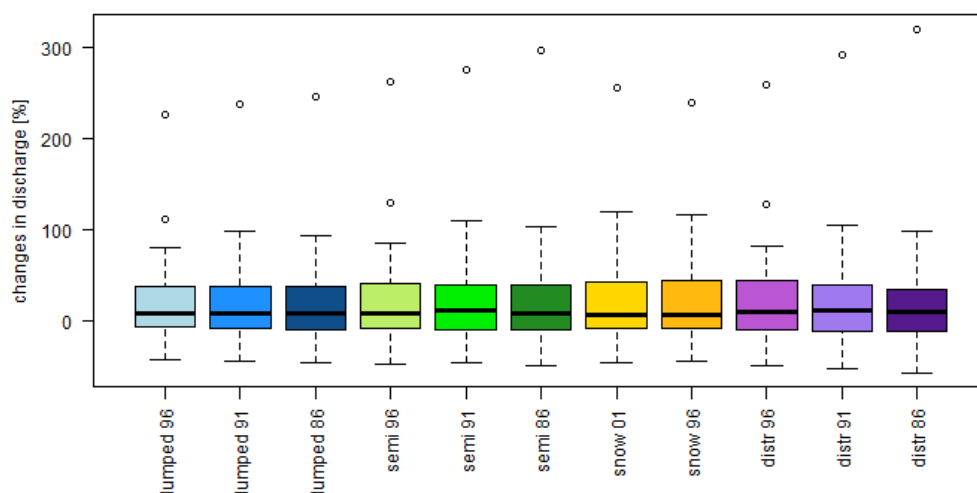
(b) EC



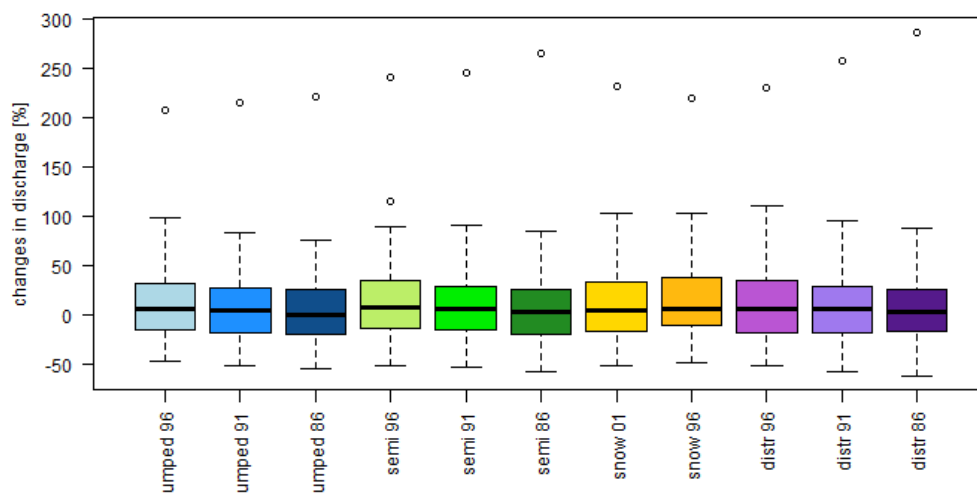
(c) GFDL



(d) MPI

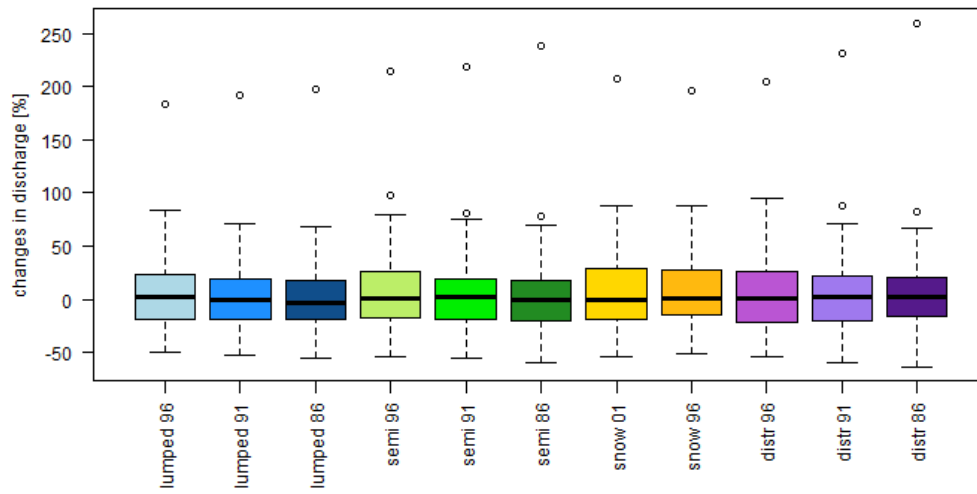


(e) MRI

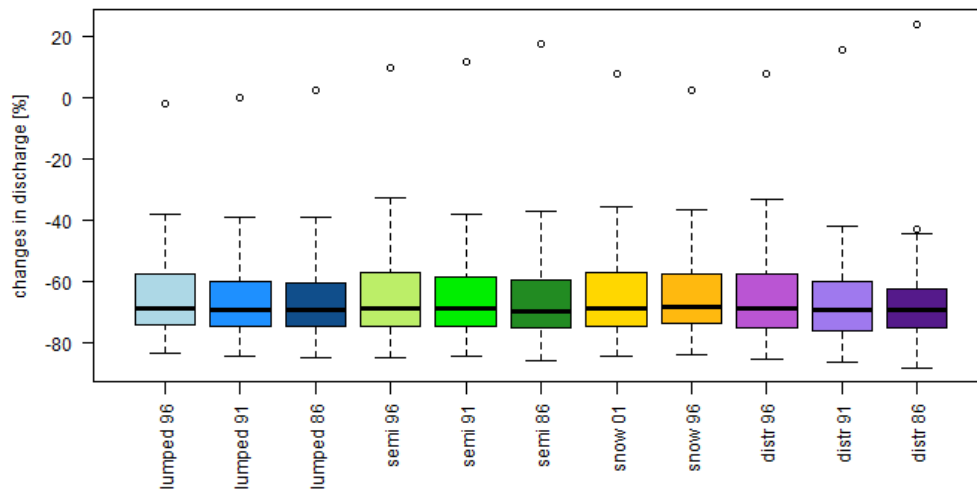


(f) TAI

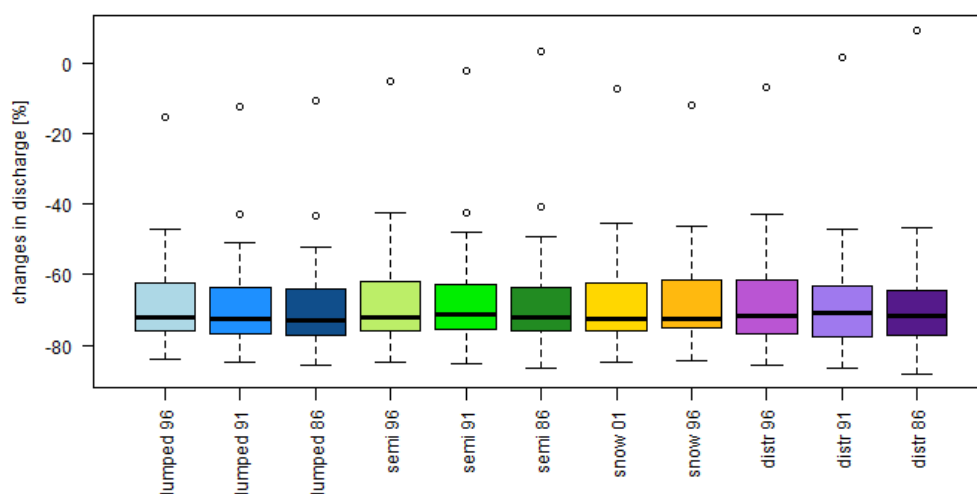
Fig. 6.72: Distribution of annual runoff changes for a 30 year period estimated from different climate models representing the green shared socioeconomic pathways (SSP126) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by different calibration variants labeled as lumped, semi, snow and distr for the different calibration periods. Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 19–49.



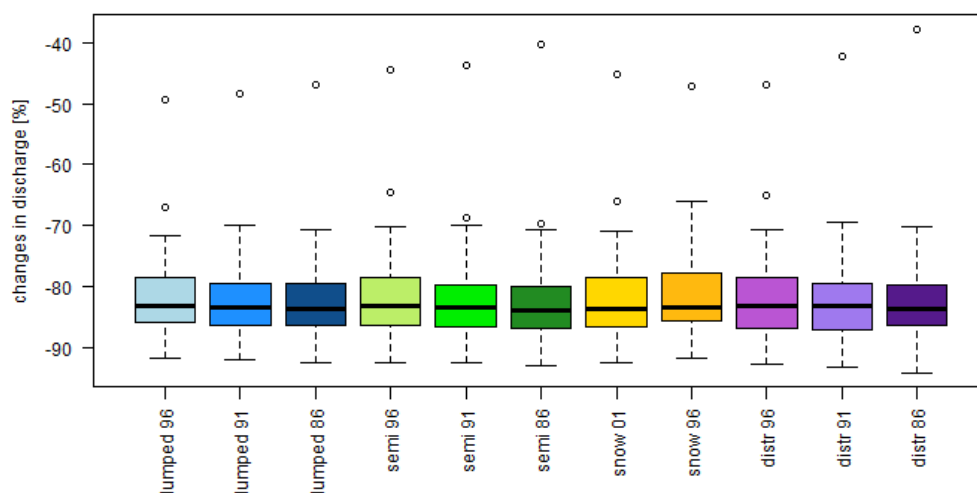
(a) CMCC



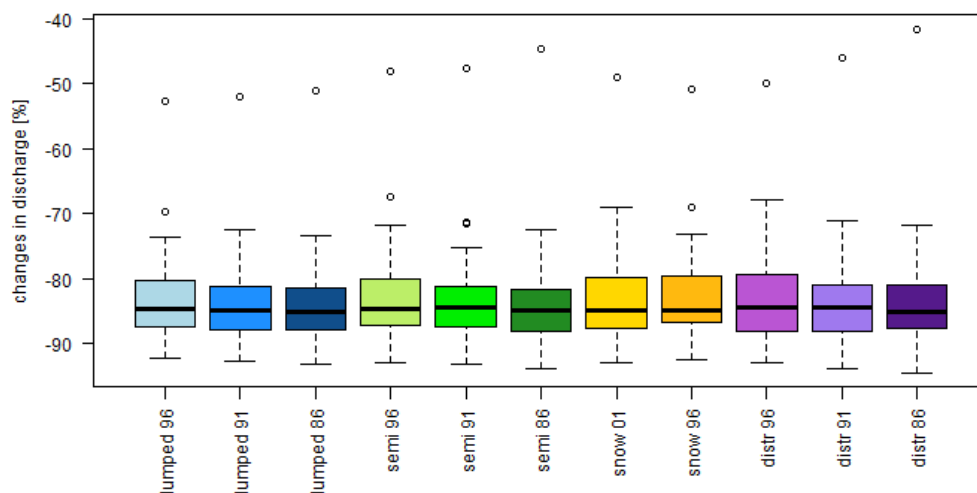
(b) GFDL



(c) MPI

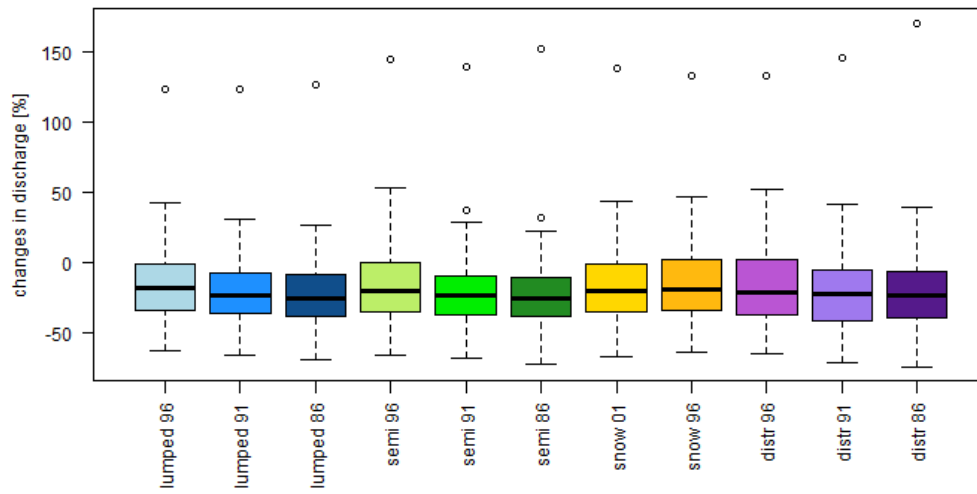


(d) MRI

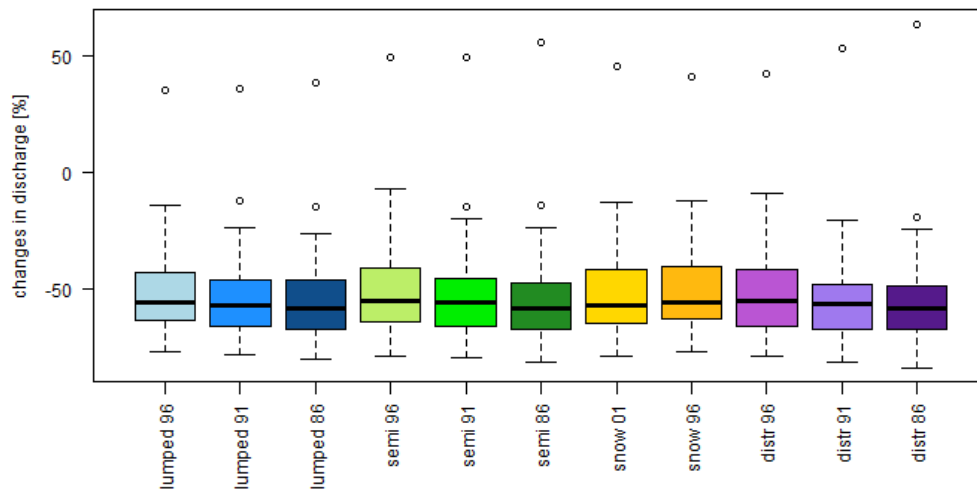


(e) TAI

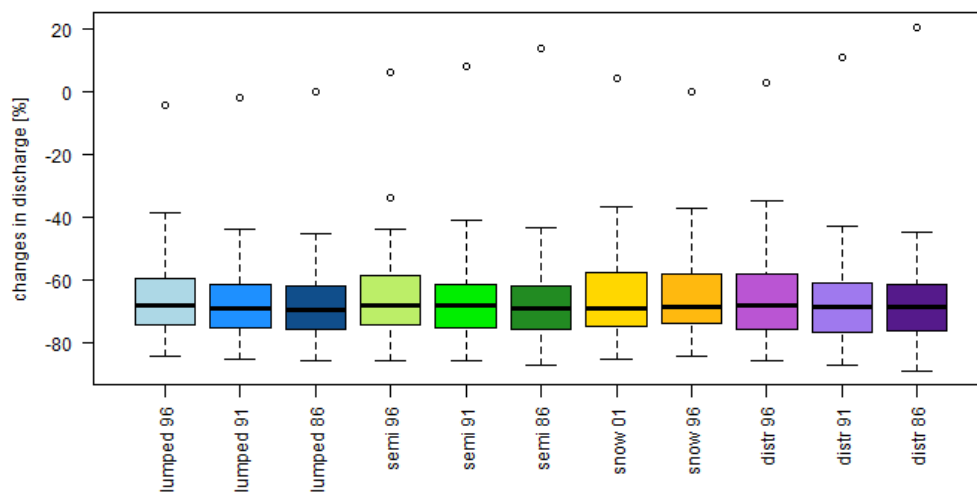
Fig. 6.73: Distribution of annual runoff changes for a 30 year period estimated from different climate models representing the the medium pathway (SSP245) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by different calibration variants labeled as lumped, semi, snow and distr for the different calibration periods. Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 19–49.



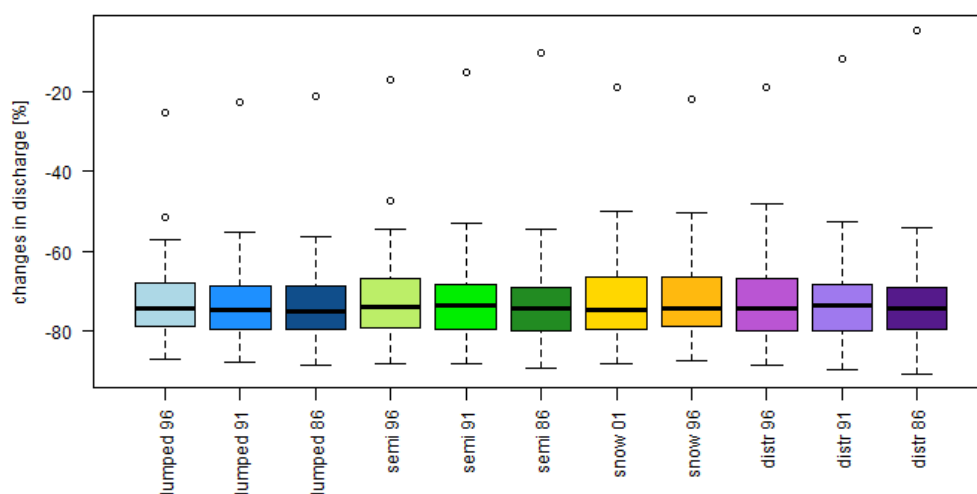
(a) CMCC



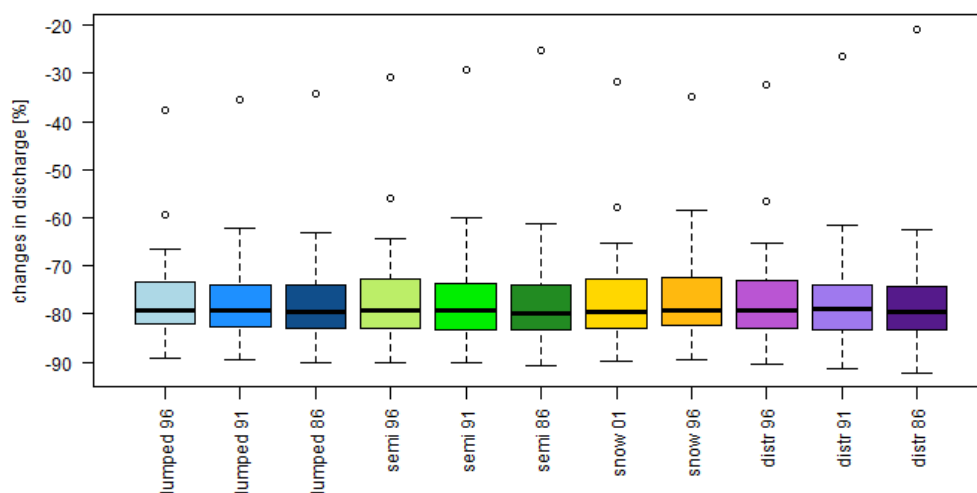
(b) EC



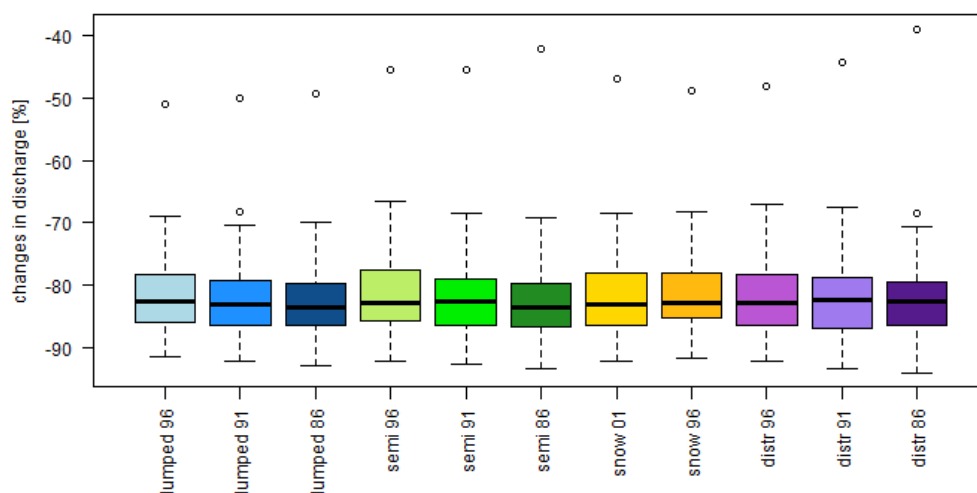
(c) GFDL



(d) MPI

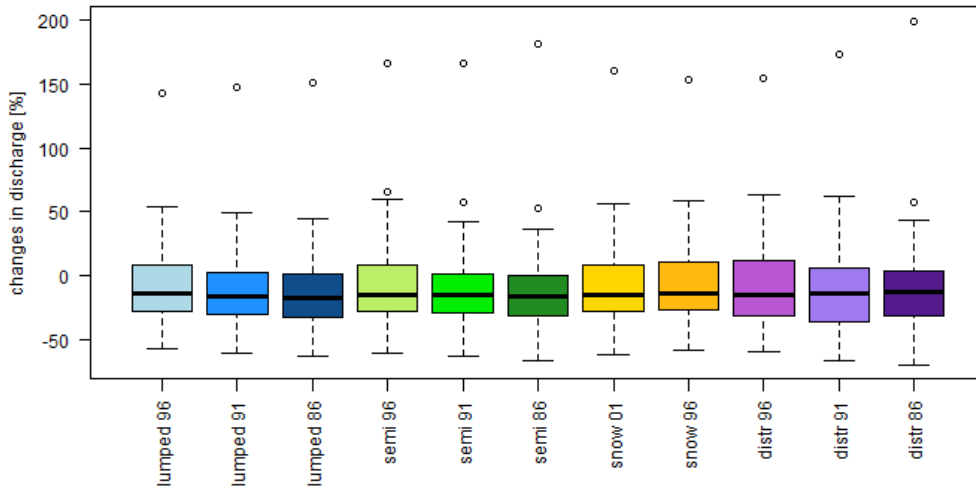


(e) MRI

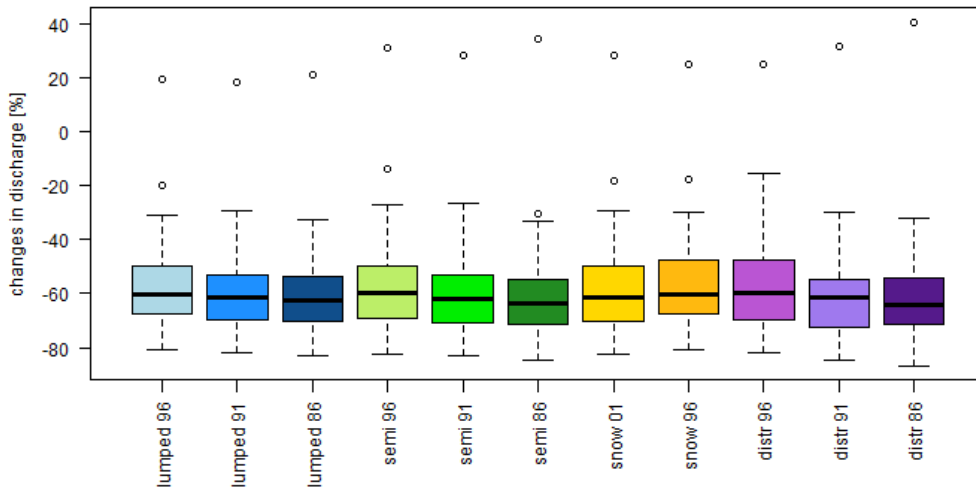


(f) TAI

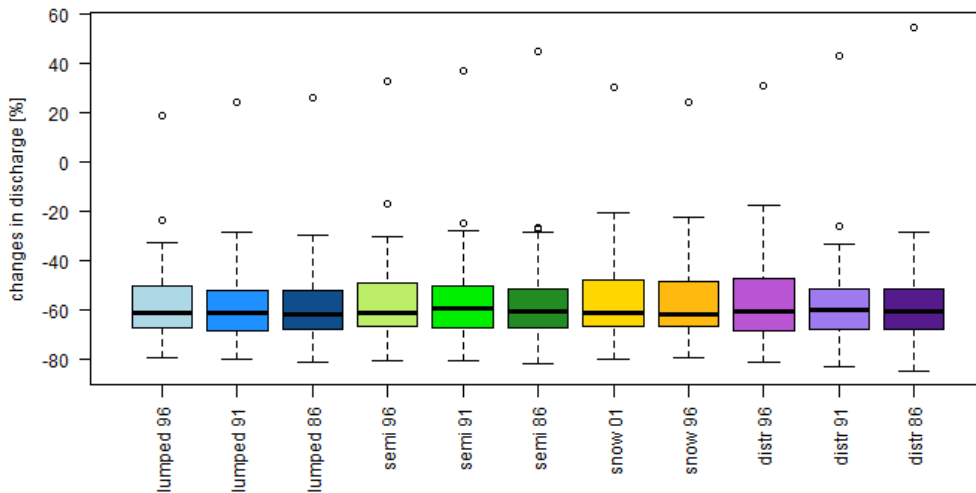
Fig. 6.74: Distribution of annual runoff changes for a 30 year period estimated from different climate models representing the regional rivalry (SSP370) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by different calibration variants labeled as lumped, semi, snow and distr for the different calibration periods. Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 19–49.



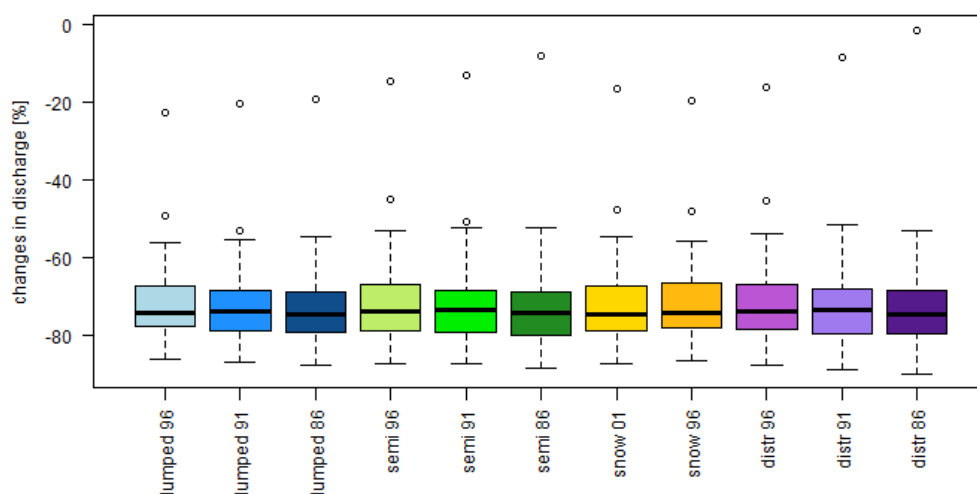
(a) CMCC



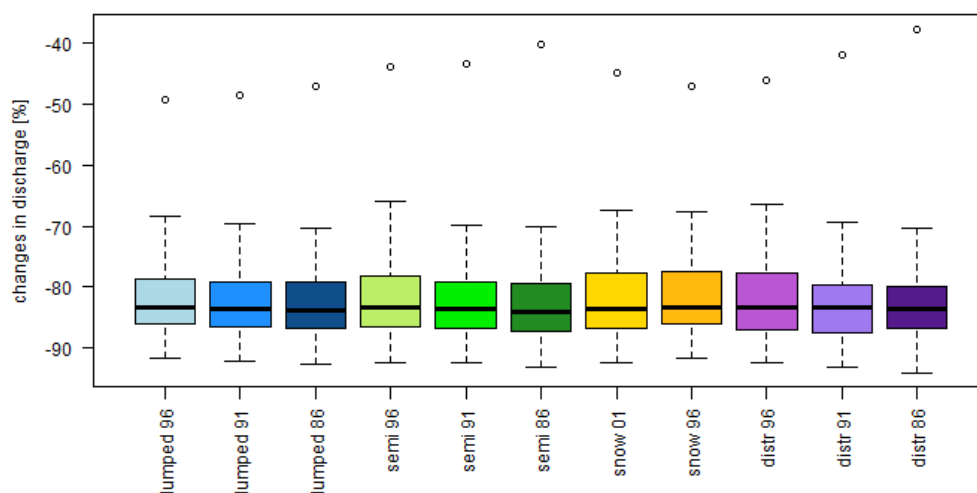
(b) EC



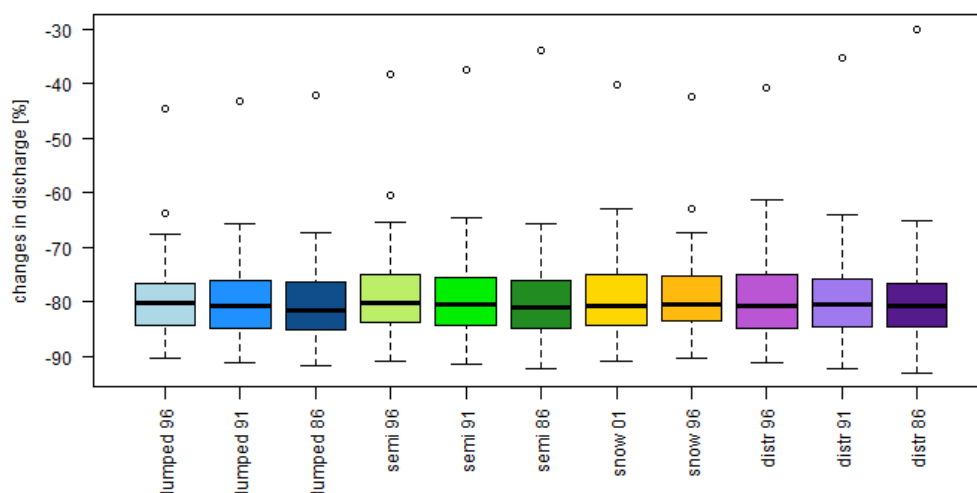
(c) GFDL



(d) MPI



(e) MRI



(f) TAI

Fig. 6.75: Distribution of annual runoff changes for a 30 year period estimated from different climate models representing fossil-fueled development (SSP585) as defined by Böttinger and Kasang (n.d.). Projections are simulated using model parameters estimated by different calibration variants labeled as lumped, semi, snow and distr for the different calibration periods. Boxes indicate 25 and 75 percentiles, whisker maximum and minimum values for changes in discharge for selected basins in Thaya catchment excluding outliers. Number of basins depends on calibration variant and period and is between 19–49.