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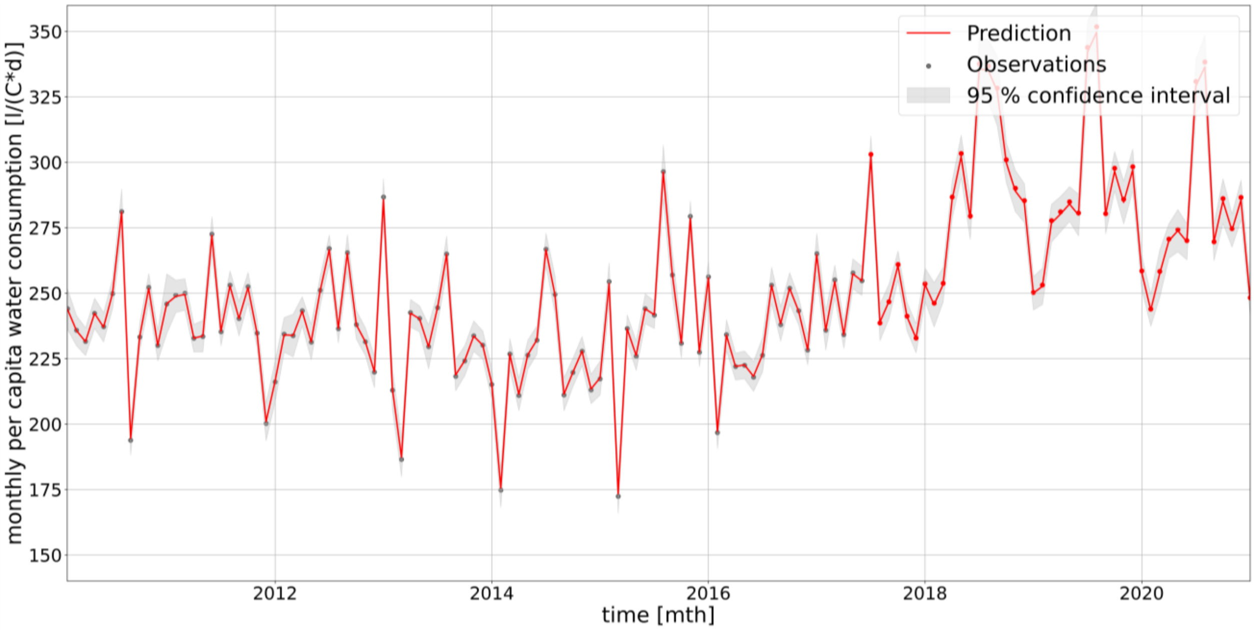

Risk analysis of climate change impacts on the quantitative drinking water supply

Master's thesis in Water Supply

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Department of Architecture and Civil Engineering

CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2022
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MASTER’S THESIS ACEX30

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Master’s Thesis in the Master’s Programme Infrastructure and environmental engineering

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Institutionen för arkitektur och samhällsbyggnadsteknik
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Cover:
Gaussian process regression used to project the future water demand
Department of Architecture and Civil Engineering
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ABSTRACT

As the construction, maintenance and expansion of water supply systems require considerable investments and their operational flexibility is only given to a certain degree, special attention should be paid to ensure that the system components are designed for a long service life so that the future water demand can be met. For this purpose, future water supply parameters, for instance, the daily peak demand and various other factors must be determined. In past decades, when determining supply parameters little to no consideration was given to the negative impacts of climate change on the supply situation. As a result, past heat summers, such as those in 2018 or 2022, have pushed water supplies to their limits in much of Germany. Therefore, in the context of this thesis, a risk analysis is conducted with the aim of determining the future water demand in Southern Germany. In order to achieve this, a surrogate model that is based on a machine learning approach and operates on the basis of Gaussian process regression is applied. The results generated in this process are used to set up an early warning system, which can be used by the water utility companies of the study area to determine their future water balance and to assess whether the water resources at their disposal will be sufficient to provide the necessary future water demand. Furthermore, the early warning system can be used to investigate the effect of planned countermeasures. In addition to the early warning system, a catalog of measures was compiled, which should serve as a guide in the successful adaptation of water supply systems to the negative effects of climate change.

Key words: water demand, climate change, climate projections, machine learning, Gaussian process regression

Contents

Preface

This master thesis of 30 ECTS was carried out at the Department of Architecture and Civil Engineering as part of the master's program Infrastructure and environmental engineering program, Chalmers University of Technology, Sweden and at the Institute for Modelling Hydraulic and Environmental Systems as part of the master's program Water Resources Engineering and Management, University of Stuttgart, Germany.

This thesis is also a part of the internal research project "Influence of the climate change on the drinking water supply" of the consultancy firm RBS wave GmbH.

This part of the project has been carried out with Ivan Starcevic as a researcher and Dr. Ilja Kröker as a supervisor at the University of Stuttgart and Dr. Esad Osmancevic as supervisor at the company. The examiner at Chalmers of this master thesis is Thomas Pettersson.

I would like to thank the examiner, the supervisors and everybody else who guided and advised me during my master thesis. I would also like to thank RBS wave GmbH for their cooperation and involvement.

Göteborg, November 2022

Ivan Starcevic

Notations

Roman upper case letters

D	dataset
E	expectation
ET_a	actual evapotranspiration
GP	Gaussian process
GWR	groundwater recharge
K	$n \times n$ covariance matrix
K_*	$n \times n_*$ covariance matrix
K_v	modified Bessel function
N	Gaussian Normal distribution
P	Precipitation
Q_D	fast runoff component
$Q_{d,m}$	average daily demand
$Q_{d,max}$	peak daily demand
R^2	coefficient of determination
$WB_{climatic}$	climatic water balance
X	design matrix
X_*	matrix of the test data

Roman lower case letters

$d()$	Euclidean distance
f	output of training data
f_d	daily peak factor
f_*	output of test data
$f(x)$	output variable of observed data points
$f(x')$	output variable of the to be predicted data points
$k()$	covariance function
l	characteristic length scale or correlation length
$m()$	mean function
n	number of observations
v	parameter of Matern kernel
x	input variable of observed data points
x'	input variable of the to be predicted data points
x_1	maximum monthly temperature
x_2	monthly average temperature
x_3	monthly precipitation rate
x_4	number of hot days per month
x_5	number of summer days per month
x_6	number of ice days per month
x_7	monthly climatic water balance
x_8	number of the month
y_i	measured or observed value
$\bar{y}$	mean value
$\hat{y}_i$	predicted value

Greek upper case letters

$\Gamma()$	gamma function

Greek lower case letters

$\delta_{xx\prime}$	Kronecker delta
ε	noise
μ	covariance functions
${\sigma_n}^2$	noise variance
${\sigma_f}^2$	signal variance

Acronyms

IPCC	Intergovernmental Panel on Climate Change
UN	United Nations
GWS	German Weather Service
ANN	Artificial neural network
SDG	Sustainable Development Goals
EU	European Union
DIN	Deutsches Institut für Normung
DVGW	Deutscher Verein des Gas- und Wasserfaches
RCP	Representative Concentration Pathway
GRACE	Gravity Recovery And Climate Experiment
GRACE-FO	Gravity Recovery And Climate Experiment-Follow On
NASA	National Aeronautics and Space Administration
DMA	District Metered Area
MLR	Multivariate linear regression
ARIMA	Autoregressive integrated moving average
GPR	Gaussian process regression
SE	Squared exponential
RBF	Radial basis function
NSE	Nash-Sutcliffe model efficiency coefficient
GPL	Variable notation for something
CZ	Climate zone
S.G.	Southern Germany
WUC	Water utility company
HU	Hydrogeological unit

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1 Introduction

1.1 Background

“For [water] it is the chief requisite for life, for happiness, and for everyday use.” Morgan (1914)

Water is an indispensable basis of all life and has always played a decisive role in the socio-cultural, political, and economic development of civilizations, as has been recorded by the ancient Roman engineer and architect Marcus Vitruvius Pollio in his work De architectura. It is therefore not surprising that a vast majority of early agricultural sedentary human settlements, such as the ones in the Tigris-Euphrates and Nile valleys, were erected in close vicinity to rivers, which did not only provide a means for the transportation of goods and the irrigation of crops, but especially guaranteed a safe and continuous source of fresh drinking water (Laureano, 2013). As humanity progressed great efforts were made to implement technical systems, e.g., the Roman aqueduct system, to ensure a safe and continuous supply of drinking water (Aicher, 1995). Nowadays water supply systems have evolved into highly complex networks, which often have grown over many decades and must constantly be adapted to changing requirements in order to ensure a secure and reliable supply of drinking water (RBS wave GmbH, 2017). One such changing requirement, which harms the qualitative and quantitative composition as well as the continuity of the drinking water supply and consequently substantially risks its safety, are the changes of the prevailing climatic conditions due to climate change. The extent of the impact climate change has had on the water supply could be observed in recent years, when exceptionally hot and dry summers, such as the ones in 2018 and 2022, have not only caused entire rivers and streams to dry up, contributing to crop failures and production stoppages, but also posed a major challenge for water utility companies in Germany, as many of them faced supply shortages (Imbery et al., 2018).

Increases in the recorded temperatures, with the global average annual temperature in the decade from 2010 to 2020 being 1.1 °C above the average from 1850 to 1900 according to the Intergovernmental Panel on Climate Change (ICPP) as well as the observation of more frequent dry spells and droughts, lead to dried out and therefore less water absorbent soil, contributing to declining groundwater recharging rates and spring discharges, which thus, due to a lack of availability, increases the risk of disruptions in the water supply (Intergovernmental Panel on Climate Change, 2021). In addition to diminishing water sources, a correlation between water consumption and increasing temperatures as well as dry spell periods could be established, consequently exerting additional pressure on the raw water sources. On the one hand, this can be observed by the fact that water withdrawals for irrigated agriculture, which currently add up to 70% of the water extracted worldwide, are expected to increase by more than 50% across the world by 2050, due to a more rapid depletion of the soil moisture content of agricultural land (United Nations, 2021). On the other hand, this tendency is also recognizable in Germany where the average per capita water consumption has shown a proclivity to fall since the beginning of the 1990s, but irregularly warm and dry summers have led to a reverse of the trend in recent years (Bundesverband der Energie- und Wasserwirtschaft, 2022).

Along with the negative effects of climate change, an increasing global population, economic development, and changing consumption patterns have altogether led to the increase of the global water demand by a factor of six over the last century. This development is expected to proceed with a steady annual rate of +1.0% (United Nations, 2021). The previously mentioned factors, which lead to a decrease of the raw water renewal rates and an increase in the water demand, consequently, contribute to a progressively growing risk of water stress, even in regions where water resources are still considered to be abundant today. This is evident by the fact that according to the "World Water Development Report" of the United Nations, the number of people living in areas that are potentially water-scarce at least one month per year is expected to rise from 3.6 billion in 2018 to roughly 4.8 – 5.6 billion by 2050 (World Meteorological Organization, 2021).

1.2 Aim and objectives

There are numerous climate projections reliably predict the development of the global and regional climate over the next few decades, but although the connection between climatic parameters and their impacts on water availability and drinking water consumption have already been established and characterized in theory, statistical and reliable projections of the actually expected drinking water demand in the decades to come are often missing. For this reason, water utility companies face the major challenge of properly assessing whether the available water sources are adequate to guarantee the provision of hygienically safe drinking water with sufficient pressure and in sufficient quantities in the future, while operating as cost-effectively as possible and ideally using and maintaining local water resources, which constitutes the purpose of every water supplier (RBS wave GmbH, 2017).

The aim of this thesis is therefore to conduct a risk analysis to determine the impact climate change is expected to have on the future drinking water demand in Southern Germany. Furthermore, as part of risk management, appropriate measures to counteract the negative effects of climate change on the water supply should be identified. For this purpose, in the first step, it should be established how well the water consumption can be determined based on climatic factors. In order to achieve this, measured climatic and supply-related data from 60 water supply companies in Southern Germany and from weather stations of the German Weather Service (GWS; German: Deutscher Wetterdienst), which was collected within the framework of an internal research project of the consultancy firm RBS wave GmbH, was analyzed with the help of a surrogate model that is based on a machine learning approach and operates based on Gaussian process regression. In the next step, climate projections from the German Weather Service, which are based on different climate scenarios, were incorporated into the surrogate model and used to determine the future water demand in the study area. The results generated in this process as well as projections about the future availability of local water sources were then used to set up an early warning system, with which the future water balance of an individual water utility company located in the study area as well as the effects of planned countermeasures can be determined and illustrated. Most importantly the early warning system also indicates the point in time at which the water demand can no longer be met from the company's own water resources.

In addition to the early warning system, a catalog of measures was compiled in cooperation with the investigated water supply companies, which should serve as a guide in the successful adaptation of water supply systems to the negative effects of climate change. The findings as well as the therefrom resulting early warning system and catalog of measures developed in the scope of this thesis are intended to make water utility companies aware of the impacts of climate change on their supply systems, assist them in adapting to the consequences of climate change in a timely manner, and provide them with a tool with which they can point out the seriousness of the situation to local politicians and residents and encourage them to rethink their political decisions and consumption behavior.

1.3 Limitations

This thesis was conducted as part of a research project, which aims at analyzing the influence of climate change on the drinking water supply in Southern Germany. Within the framework of this thesis Southern Germany is defined as the territory made up of the five federal states Baden-Württemberg, Bavaria, Rhineland-Palatinate, Saarland and Hesse. The scope of the study was limited to everyday water demand while excluding the impacts of climate change on the water supply caused by extreme weather events such as forest fires and flood events. For this purpose, climatic data from weather stations and supply-related data from water utility companies were collected. Due to the limited size and availability of the data basis, the machine learning approach was limited to the method of Gaussian process regression, which can provide reliable results even in data-poor settings. Other methods such as artificial neural networks (ANN) on the other hand require large datasets to provide reliable results and therefore could not be implemented. During the analysis and calculations confounding factors that prevented conclusions from being drawn about the effects of climate change on future water demand were identified. These include data gaps, measurement inaccuracies, high water losses in the supply system, a high proportion of large-scale consumers and a pronounced water consumption during the winter months caused by winter sport tourism. For this reason and due to time restrictions not all available datasets could be evaluated in the scope of this thesis. Another limiting factor in connection to the available data in the context of this thesis is the composition of the available supply-related data, which consists of monthly consumption values. A finer breakdown of the data would enable the supply-related parameters to be assigned more precisely to individual weather events, which would help to improve the accuracy of the projections. The projections were moreover limited by the availability of climate projections. Since small-scale, local climate projections were not available, the regional climate projections for Southern Germany were adjusted to the individual climatic conditions of the supply areas of the participating water utility companies. The climate projections used for this thesis extend over a period of 70 years (2021-2090). Therefore, the projections of future water demand are also limited to aforementioned time period.

1.4 Summary of the work plan

In the scope of this thesis the following steps were undertaken to accomplish the objectives described in Chapter 1.2:

- Research of scientific literature and the analysis of projects, that used similar methods: The scientific literature was selected in order to gain basic knowledge and an understanding of the subject as well as to support the implementation of the selected machine learning method.
- Data processing: The sorting and analysis of climatic data from weather stations and supply-related data were provided by the water utility companies as well as

the requirement and the adjustment of projected climatic data for the projection of the future water demand.

- Programming of the machine learning approach: This step included the learning of the programming language Phyton as well as the application of the obtained skillsets to implement Gaussian process regression.
- Carrying out of calculations: Determining of the climate sensitivity of each water supply company. Calculation of the future water demand and further evaluation for the climate-sensitive water supply companies, resulting in a projection for the entire climate zone.
- Development of an early warning system and a measure catalog: Evaluation of the effects of climate change on the quantitative supply situation of drinking water supply systems as well as the development of suitable countermeasures and adaptation strategies in cooperation with the participating water supply companies.

1.5 Report Overview

Figure 1 serves as a guide of the structure of the thesis report and its content.

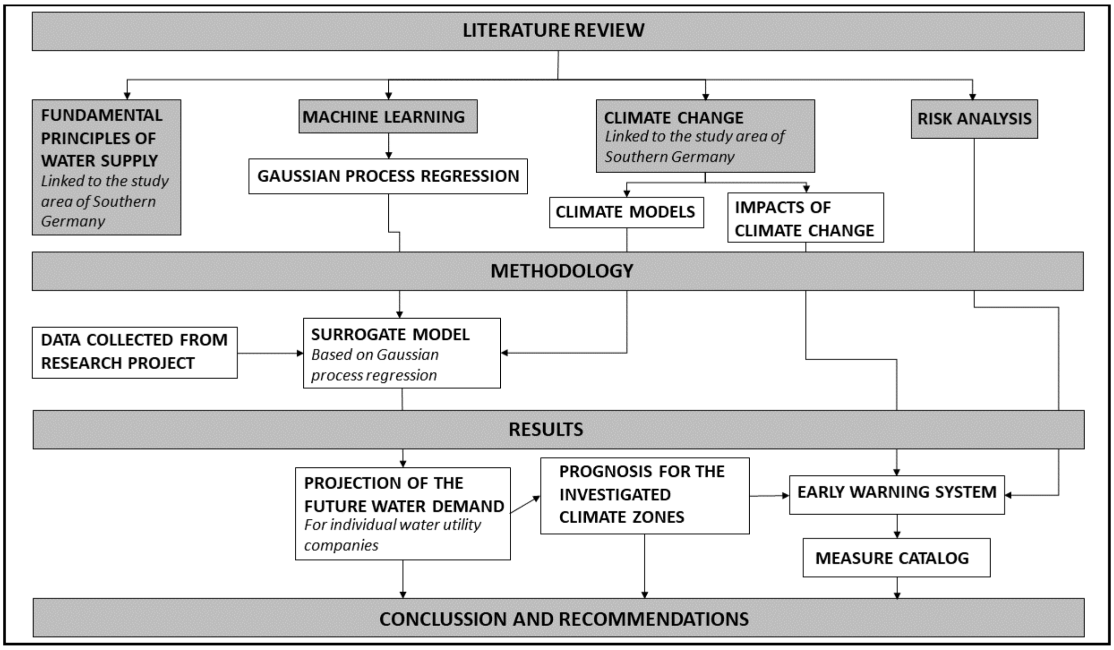


Figure 1 Schematic diagram of the thesis report

2 Literature review

2.1 Fundamental principles of water supply in the study area of Southern Germany

2.1.1 Legal framework and regulations

Water is often referred to as the most important nutrient. Therefore, many national as well as international laws, regulations, and resolutions are in place to protect and guarantee the safe provision of this natural resource, one of which are the Sustainable Development Goals (SDGs), which were established in 2015 by the United Nations General Assembly and are intended to be achieved by the year 2030. Among other things, 1 of the 17 set goals focuses on the availability and sustainable management of drinking water and the access to appropriate and safe sanitation for all humans, which is recorded in the SDG 6 "Clean Water and Sanitation" (United Nations, 2015). According to the United Nations, in 2020 approximately 2.2 billion people lacked safely managed access to drinking water (United Nations Children's Fund et al., 2019). The fulfilment of the sixth SDG poses a major challenge for the international community, which is threatened by the increasing magnitude and the projected developments of climate change (United Nations, 2015). Therefore, it is important to analyze the impact climate change will have on the water resources and the future water demand in order to be able to adapt the supply systems to the changing conditions and to develop countermeasures against the negative effects of climate change at an early stage.

In addition to the SDGs, there are further legislative regulations within the European Union that regulate the handling and supply of water sources, waterways and drinking water. One such legislative regulation is called "Water Framework Directive 2000/60/EC" and was implemented by the European Union (EU) in 2000. This directive legally binds the member states of the EU to achieve a good qualitative or chemical and quantitative status of water bodies, including surface waters, transitional waters, coastal waters and groundwaters. The directive entered into force in December 2000. Its main goal is the enhancement of the state of ecosystems, the reduction of the pollution of the groundwater as well as the reduction of priority substances in water bodies. Furthermore, it aims at the sustainable use of water resources and at reducing the impact of flood events and droughts. The member states of the EU were obliged to implement the specifications of the directive into national law (European Parliament et al., 2014).

Another directive of the European Union (EU) is the "Drinking Water Directive 2020/2184", which was revised in 2020 and dictates the essential quality standards for drinking water intended for human consumption. The directive entered into force in January 2021. The directive's standardized requirements are designed to prevent any harmful effects contaminated drinking water can have on the human health and are applied to distribution systems which supply drinking water to more than 50 people or more than 10 m³ of drinking water per day, drinking water in bottles, containers and from tankers, as well as water used in the food-processing industry. The requirements include a total of 48 microbiological, chemical and indicator parameters, which are to be observed and tested in regular intervals. The member states of the EU were obliged to implement the specifications of the directive into national law, while also possessing the ability to implement further requirements, such as additional parameters or stricter limit values (European Parliament et al., 2020). In addition to setting qualitative limit values for drinking water intended for human consumption and by monitoring these to assure the set requirements are met, the directive also dictates preventive measures, which have the purpose of identifying potential risks and weak points in the supply chain that potentially could have a negative impact on the drinking water quality. To achieve that goal, it is foreseen that the water suppliers implement a holistic approach, which does not only focus on the supply network, but rather on the analysis of the whole supply chain including all steps and processes from the catchment area to the point of consumption. According to the directive, the effects of climate change and the associated risks therefrom should be taken into special consideration when analyzing the supply chain. The risk analysis of all the affected drinking water supply systems is to be finalized no later than January 12, 2029. From this date onwards, the risk analysis should be carried out in regular periods of maximum 6 years and should be revised and updated if needed (European Parliament et al., 2020).

As a member state of the General Assembly of the UN and the EU, Germany is legally obliged to implement the established goals and regulations into national laws.

The resolutions of the EU drinking water directive were implemented into German national law through the introduction of the German drinking water ordinance (German: Trinkwasserverordnung), which was enacted in 2001. It sets the legal framework for the quality standards of drinking water for human consumption. Its main goal is to ensure that no damage to human health results from the consumption of the provided drinking water. The German drinking water ordinance also refers to the technical regulations for compliance with the generally recognized rules of technology (German: Allgemein anerkannten Regeln der Technik) (Bundesministerium der Justiz, 2021).

One of these regulations is the DIN 2000 standard, which defines the main principles of drinking water provision. These include the quality and quantity as well as the continuity of the supplied drinking water. According to the DIN standard the quality of the drinking water needs to be such that it can be described as appetizing, stimulating enjoyment, colorless, clear, cool, and impeccable in terms of smell and taste, when it reaches the consumer. Furthermore, another integral component of the DIN 2000 standard is the ensurement of the supply of hygienically safe drinking water to the population and other users, taking into account ecological and economic aspects (Deutsches Institut für Normierung, 2000).

2.1.2 Structure of the drinking water supply in Southern Germany

According to the Federal Office of Statistics (German: Statistisches Bundesamt) in 2016, a total of 4,258 water utility companies, with a discharge of more than 1,000 m^3/a, extracted 2,214.0 million m^3 of raw water for the drinking water provision in Southern Germany, from which 1,936.5 million m^3 were provided to the end consumers. The consumption of end consumers can be divided into the consumption of the households and small businesses, which amounts to approximately 82.0% of the total water supplied to the end consumers, and into the consumption of the industry, which amounts to approximately 18.0% of the total water supplied to the end consumers. The difference between the amount of raw water extracted and the amount provided to the end consumers can be divided into the water consumption for the own usage of the water utility companies and water losses due to measurement errors and leakages in the supply system. The water for own usage amounts to 50.4 million m^3, while the water losses amount to 227.1 million m^3 (Statistisches Bundesamt, 2019).

In addition to the public water utility companies in Germany, there are also private water utility companies, which operate systems for the extraction of raw water and supplying drinking water to their customers and often include companies from various sectors such as the agricultural or industrial sector. There are no official statistics on the water consumption of the private water utility companies. The water quantities provided by the privately owned water utility companies are not included in the statistics presented.

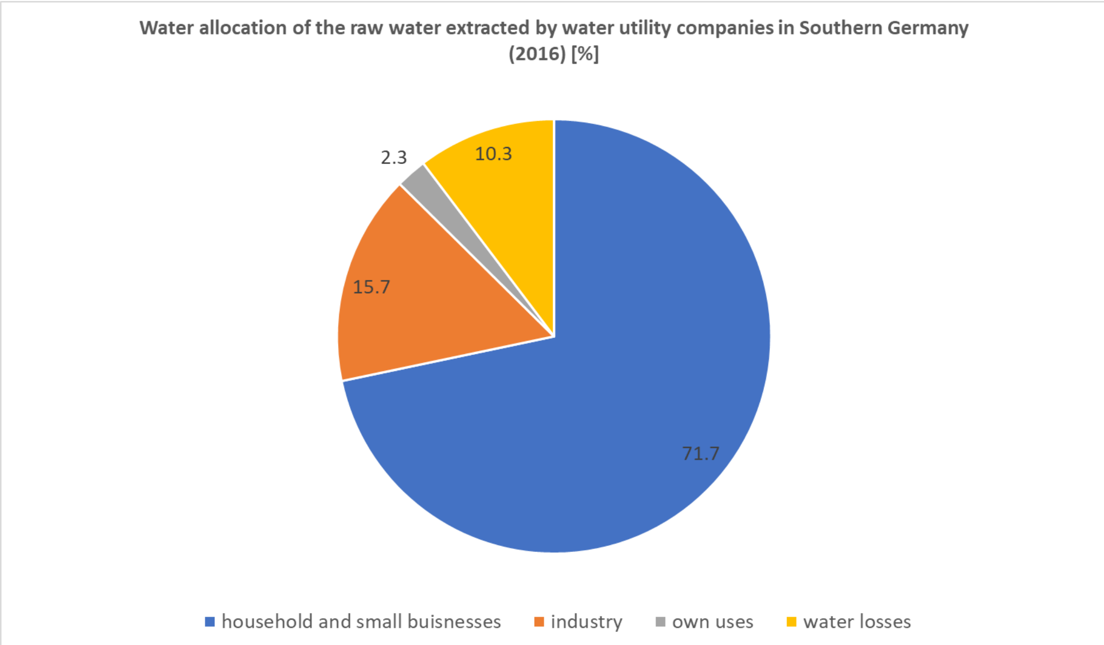


Figure 2 *Water allocation of the raw water extracted by water utility companies with a discharge of more than 1,000 m³/a in Southern Germany for the year 2016 based on the report from Statistisches Bundesamt (2019)*

The groundwater resources are of particular importance for the public water supply in Southern Germany, since they accounted for 67.3% of the total drinking water supplied through public utility companies in 2016 (see Figure 3). Together with spring water and the enriched groundwater, it makes up more than 85.0% of the total water supplied. In comparison, the provision by surface water amounts to 7.8%. In 2016, around 34.8 million residents in Germany were connected to the public water supply. This corresponds to a connection rate of 99.6%. The average per capita water consumption in Southern Germany in 2016 was 125 l/(C*d), which in addition to water consumption of the households also includes the water consumption of small businesses, such as bakeries and butchers. At 125 l/(C*d), the per capita consumption in Southern Germany is slightly higher than the national average of 123 l/(C*d). However, water consumption levels within the individual federal states deviate from the national average value. The federal state of Bavaria, for example, has a per capita consumption of 131 l/(C*d), while the federal state of Saarland has a per capita consumption of 115 l/(C*d) (Statistisches Bundesamt, 2019).

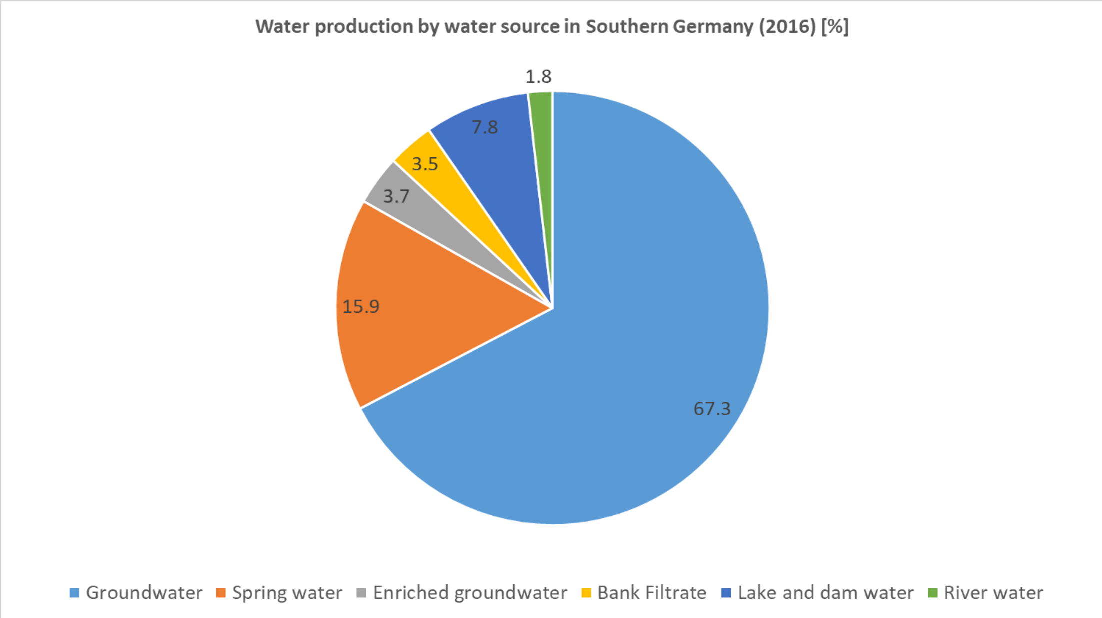


Figure 3 *Water production by water source in Southern Germany for the year 2016 based on the report from Statistisches Bundesamt (2019)*

Figure 4 shows the daily drinking water usage of German households and small businesses by the type of usage. Assuming the average per capita consumption of 125 l/(C*d) for Southern Germany, 11 l/(C*d) is accounted for by small businesses. The remaining 114 l/(C*d) of water consumed is accounted for by the households (Umweltbundesamt, 2017).

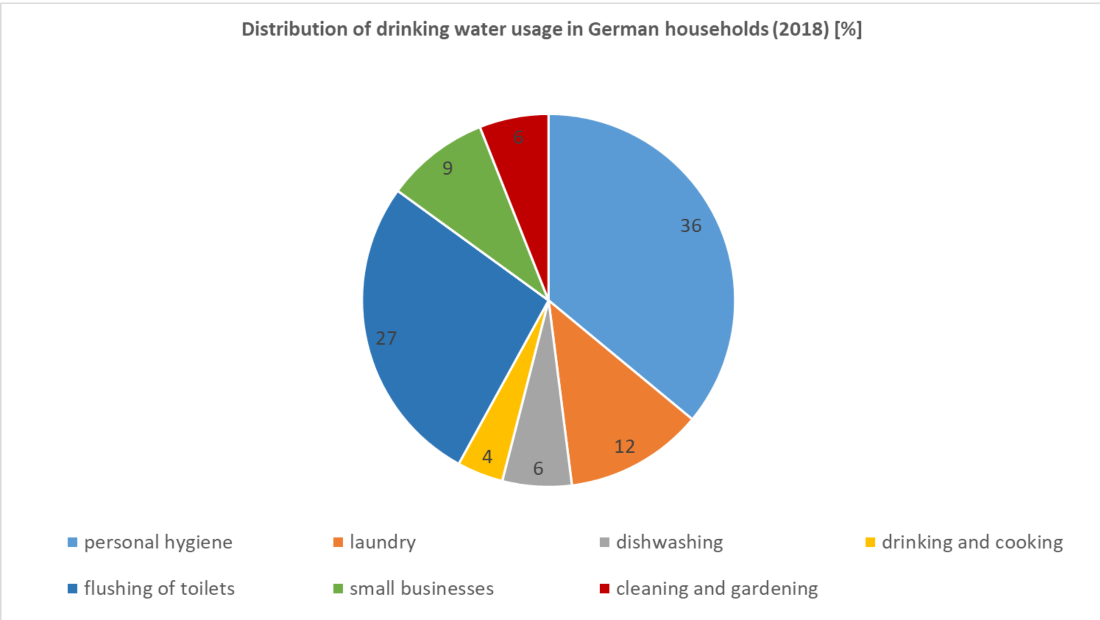


Figure 4 *Drinking water usage in German households for the year 2018 based on the figures of Umweltbundesamt (2017)*

2.2 Climate change in the study area

2.2.1 Climate change in Germany

Climate change is defined as a long-term shift of the prevailing climatic conditions, which can be impacted by natural causes, such as solar and volcanic activity, or by man-made causes, such as the emission of greenhouse gases including carbon dioxide and methane. With the beginning of industrialization in Europe in the 19th century, fossil fuels like coal, gas and oil were used on a large scale to fuel the economic development, which led to a steady increase of the effects of human activities on the state of the climate (United Nations, 2022). Nowadays, the energy, industrial and agricultural sectors are some of the main greenhouse gas emitters, with the energy sector alone, including among other things the production of electricity, transportation and manufacturing, accounting for 72.0% of all global emissions (Center for Climate and Energy Solutions, 2022). According to the sixth status report of the IPCC, climate change affects all regions of the world (Intergovernmental Panel on Climate Change, 2021). Germany is not exempt from this development and records show that climate change is already affecting the prevailing local climatic conditions (Brasseur et al., 2017). The developments related to climate change are of particular concern for the water supply sector, as climate change affects the qualitative and quantitative composition of drinking water and, therefore, according to the UN World Water Report 2020, billions of people worldwide may no longer be able to exercise their human rights to fresh and clean drinking water and sanitation (United Nations, 2020). In the following paragraphs, the relevant climatic parameters in relation to the drinking water supply in Germany will be discussed.

Air temperature

Weather records confirm that climate change is already showing its effects on the global climate conditions, as the average air temperature is already 1.1 °C warmer than in the pre-industrial era. Similar developments can also be observed for Germany. According to the German Weather Service, an average temperature of 9.5 °C was recorded in Germany in the last decade. Thus, the decade from 2010-2020 was 1.9 °C warmer than the decades from 1881-1910, when weather records were first recorded. In a global comparison, the air temperature in Germany has risen more than the global average (Deutscher Wetterdienst, 2022a). Figure 5 shows the course of the annual average temperature in Germany in the period 1881-2021.

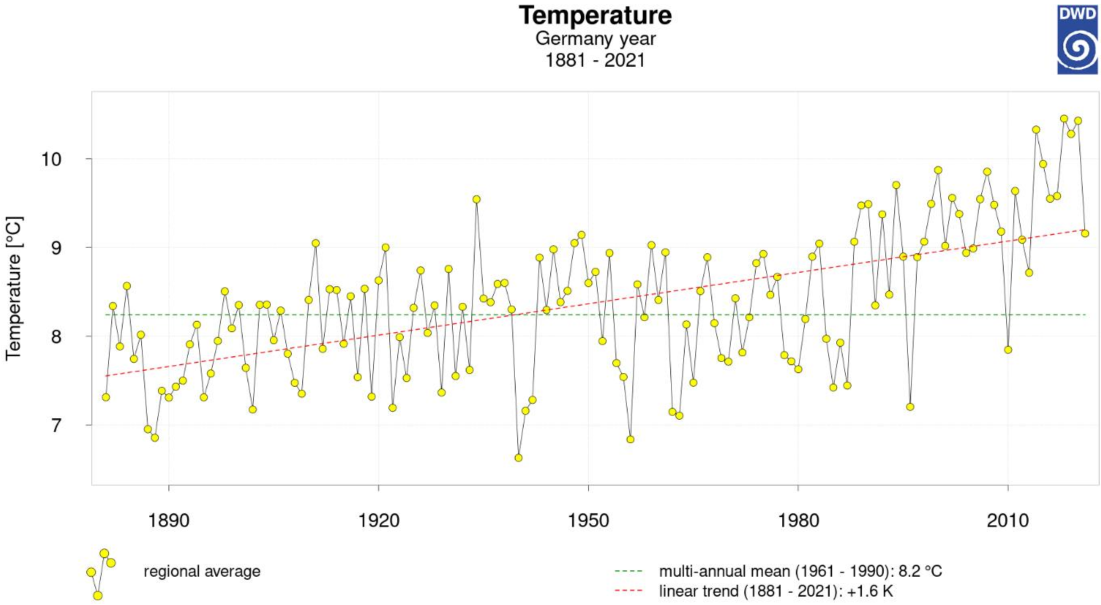


Figure 5 *Annual mean temperature in Germany in the period 1881-2021, Source: Deutscher Wetterdienst (2022b)*

A linearly increasing trend of the average temperature can be observed. Especially in the last 50 years, the temperature in Germany has risen faster than before. This is reinforced by the fact that 9 of the 10 warmest years occurred after the year 2000, with 7 occurring after the year 2010. Furthermore, according to the GWS, 2018 was the warmest year to date in Germany with an average temperature of 10.5 °C since weather records began, followed by 2020 with 10.4 °C and 2014 with 10.3 °C (Deutscher Wetterdienst, 2022b). The time period from 2010 to 2020 is characterized by further increasing average temperatures and temperature records. On average, for Germany, the years 2014, 2018 and 2020 are characterized by the warmest temperatures since weather recording began. In addition, the second warmest winter was measured in 2019/2020 and the warmest summer in 2020. The years 2010 and 2013 constitute the coolest years in the period 2010-2020, with only the year 2010 being below the long-term average (Deutscher Wetterdienst, 2022a).

Table 1 *Annual mean temperature in Germany in the period 1881-2019 according to the figures of Deutscher Wetterdienst (2022c)*

Season	Months	Time period	Temperature change [K]
spring	March, April, May	1881-2019	+ 1.6
summer	June, July, August	1881-2019	+1.5
fall	September, October, November	1881-2019	+1.5
winter	December, January, February	1882-2019	+1.5

Table 1 shows the average temperature change of the four seasons in Germany in the period from 1881 to 2019. All four season experienced the same temperature change in the observed time period, with only the temperature change in spring being 0.1 K higher than in the other seasons. The temperature change values make it clear that all four seasons have been affected by global warming to a similar extent in the past. It can be assumed that this development will be continued in the future.

Precipitation rates

Precipitation refers to the elimination of liquid or solid water particles from the atmosphere. In addition to the air temperature, precipitation can serve as another climate parameter that can be used to describe the climate of a region (Deutscher Wetterdienst, 2022d). In comparison to the development of the air temperature, a trend for the development of precipitation rates in Germany can only be recognized to a limited extent due to the high spatial and temporal variability of precipitation. Nevertheless, according to the GWS, annual precipitation rates have increased by an average of 8.0% across Germany since 1881 compared to the reference period (1961-1990). Especially during the spring and winter months, increased precipitation rates have been recorded. Precipitation rates during the winter months have increased by 26.0% compared to the reference period (1961-1990), which is how the increase in the annual precipitation rates can be explained (Deutscher Wetterdienst, 2020).

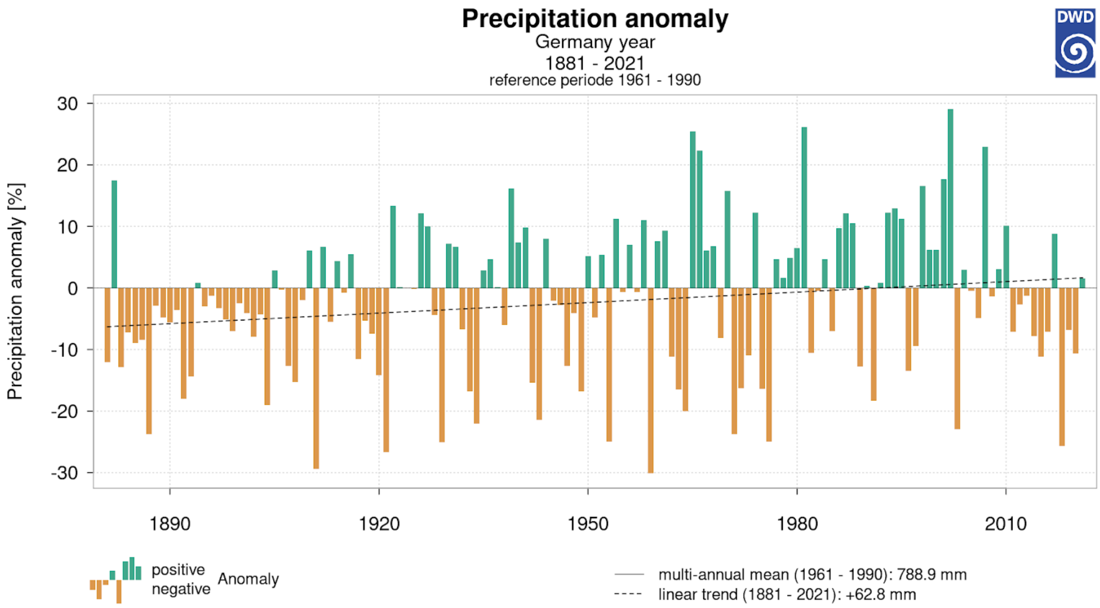


Figure 6 Anomaly of annual precipitation in the period 1881-2021 in Germany in relation to the reference period 1961-1990, Source: Deutscher Wetterdienst (2022b)

Due to the high spatial variability of the precipitation rates, it makes sense to take a closer look at the spatial distribution of the mean annual precipitation rate in Germany, which is illustrated in Figure 7.

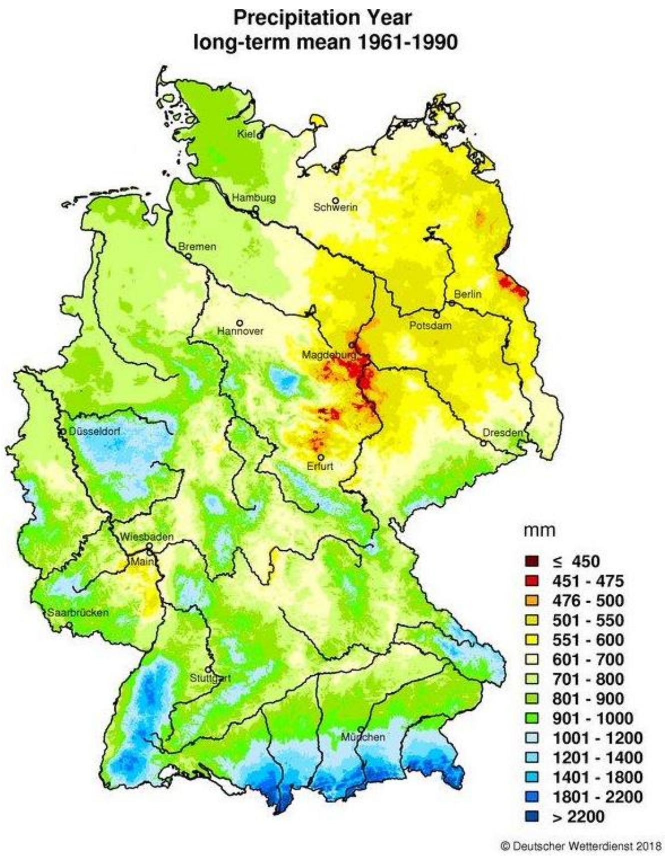


Figure 7 Long-term mean of the yearly precipitation rates in Germany for the period 1961-1990, Source: Deutscher Wetterdienst (2022e)

The map of the long-term mean precipitation rates over the period 1961-1990 illustrates the spatial variability of precipitation rates over Germany. The highest annual precipitation rates on average occur in Southern Germany, especially in the region of the Black Forest and in the Alps. There, on average, a maximum quantity of > 2,200 mm per year has been recorded over the investigated period. The lowest precipitation rates have been recorded in Eastern Germany, where minimum values of ≤ 450 mm per year have been measured. Within the study area of this thesis, the region north-east of the Palatinate Forest (German: Pfälzer Wald) is characterized by particularly low annual precipitation rates. Despite the overall upward trend in annual precipitation rates, as can be seen in Figure 6, an accumulation of low-precipitation years can be observed, especially in the study period (2010-2020). The years 2015, 2018 and 2020 are characterized by a lack of annual precipitation. Only the years 2010 and 2017 show positive deviations from the annual precipitation rates compared to the reference period.

Droughts

Droughts are defined as periods of prolonged water shortages and can last from a few months up until several years. They are affected by climatological factors such as low precipitation rates and high evapotranspiration rates caused by higher temperatures or winds (Deutscher Wetterdienst, 2022f). The following figure shows the development of the drought magnitudes in the rootable soil up to a depth of 1.8 m from 2001-2022 in Germany. The drought magnitude is used to estimate the severity of the drought, considering various influencing factors such as the duration and dryness of the drought period.

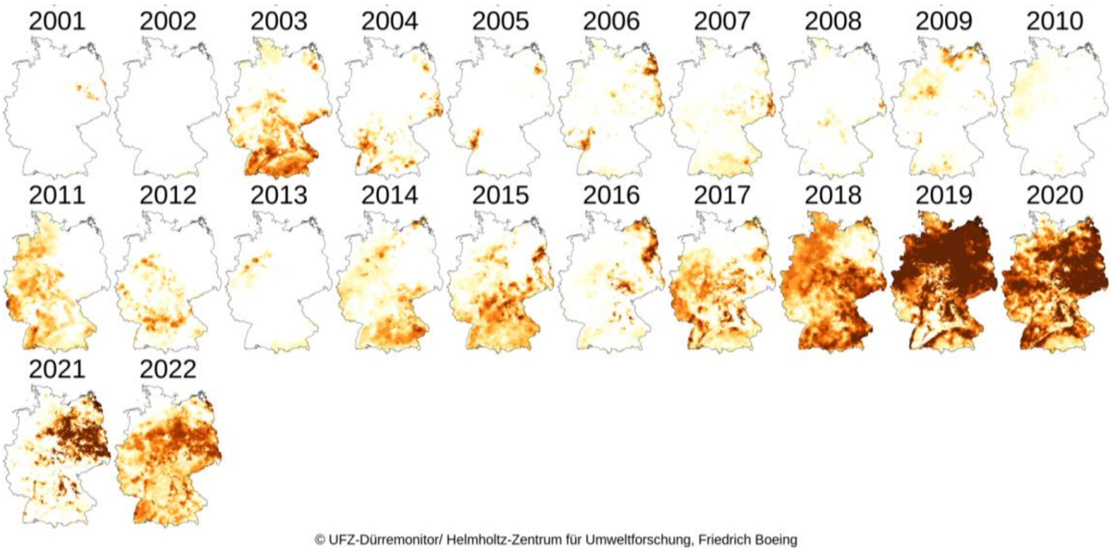


Figure 8 Development of drought magnitudes in the vegetation period April to October for soil depths of up to 1.8 m; Source: Marx (2022)

Within the study period from 2010 to 2020, one can observe that the drought magnitudes in Germany increased visibly. The trend shows a gradual annual increase in the drought magnitude since the beginning of the study period in 2010, resulting in the most severe droughts in 2019 and 2020. Especially the north-eastern part of Germany as well as parts of Southern Germany are highly affected.

The increasing number and length of droughts as a result of climate change increase the risk of low water levels in rivers and lakes, which among other things can have serious consequences for inland navigation, the industry, agriculture as well as for the water and power supply. Furthermore, it increases the risks of forest fires taking place.

Summer and hot days

A summer day is defined as a day on which the maximum air temperature is greater than or equal to 25.0 °C, whereas a hot day is defined as a day on which the maximum air temperature is greater than or equal to 30.0 °C. The number of summer days is always greater than or equal to the number of hot days. The set of summer days can also include a subset of hot day (Deutscher Wetterdienst, (2022g), (Deutscher Wetterdienst, 2022h).

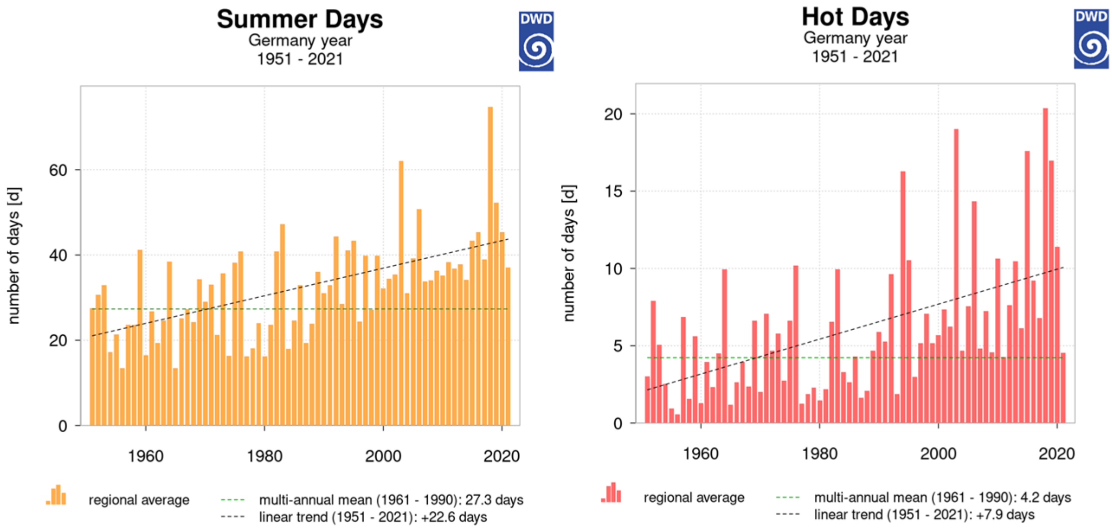


Figure 9 *Number of summer days (left) and hot days (right) in Germany in the period 1951-2021; Source: Deutscher Wetterdienst (2022b)*

Figure 9 shows the linear trend of the number of summer and hot days in Germany compared to the reference period (1961-1990). In Germany, the long-term average of summer days is 27.3 days per year and 4.2 days per year for the hot days (1961-1990). The last time these values were undershot was in 1998 and 1996 respectively. With a rise in average temperatures, the number of summer and hot days have also increased. While in the 1950s an average of 3.5 hot days per year were recorded in Germany, in the last three decades since 1991 the number of hot days increased to an average of 8.9 days per year.

Frost and icy days

A frost day is defined as a day on which the minimum air temperature is below 0 °C, whereas an ice day is defined as a day on which the maximum air temperature is below 0 °C. The number of frost and ice days serves as an indicator for the harshness of a winter. The set of frost days can also include a subset of ice days (Deutscher Wetterdienst, 2022i), (Deutscher Wetterdienst, 2022j).

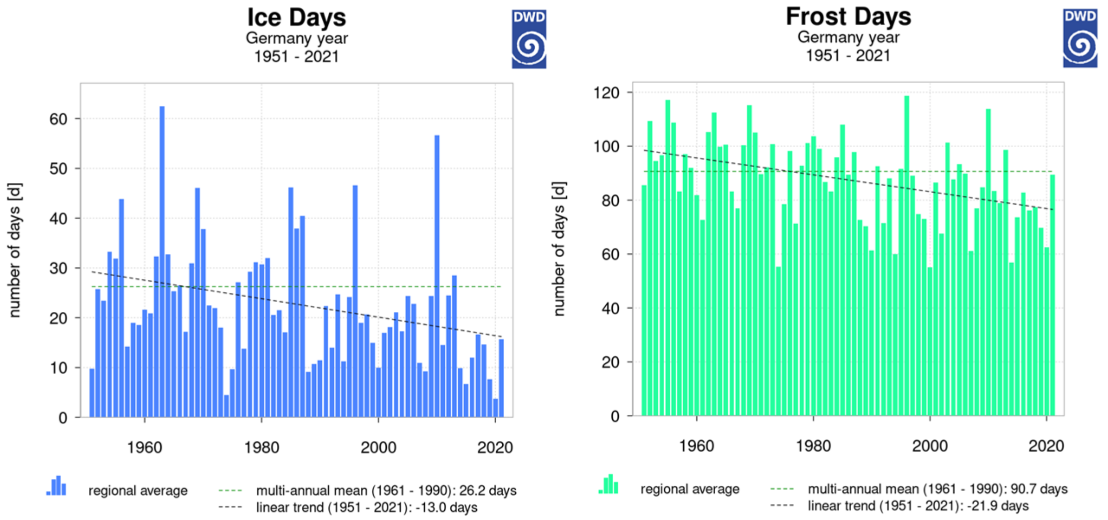


Figure 10 Number of frost days (left) and ice days (right) in Germany in the period 1951-2021, Source: Deutscher Wetterdienst (2022b)

Figure 10 shows the linear trend of the number of frost and ice days in Germany per year compared to the reference period (1961-1990). While the number of summer days and hot days are increasing as a result of climate change, the number of frost and ice days are falling compared to the long-term average of the reference period (1961-1990). In the 1950s an average of 28 ice days per year were recorded in Germany, as opposed to the last three decades since 1991, in which the number of ice days decreased to an average of 19 ice days per year.

2.2.2 Impacts of climate change on drinking water supply system

The availability, the quality and the quantity of water are not only prerequisites for human health and existence, but are essential to all aspects of our society, including the economic and industrial development, the energy production and food supply as well as the well-being of the environment and its ecosystems. The advancing effects of climate change however lead to a multitude of negative impingements on the beforehand mentioned aspects. One such negative impingement is the increase in the average annual temperature as mentioned in Chapter 2.2.1. Since the global climate and its various parameters are interlinked and influence each other, this development influences many other climatic aspects, for instance the evapotranspiration rate or the likelihood of occurrence of extreme weather events such as droughts. These as well as other developments and the resulting water scarcity pose a major challenge for the sustainable management of water resources, particularly in regions that are already experiencing water-stress today. Furthermore, numerous ecosystems, such as forest and wetlands, have already been affected by and are experiencing the negative impacts of climate change. This is of particular concern, as this not only leads to the loss of these ecosystems and hence a decline in biodiversity but also to the loss of the associated ecosystems services, for instance the water storage and purification, which in turn directly impacts the water availability, the water quality, and the water quantity. Therefore, the impacts of climate change need to be analyzed and studied and adaptation and mitigation strategies need to be developed in order to maintain public life and to preserve the affected ecosystems (United Nations, 2020).

The chapter focuses on the expected and already observed impacts climate change has and has had on the quantitative aspects of the drinking water supply in Germany.

Drinking water consumption and demand

The global water consumption has increased sixfold over the last century and due to the negative effects of climate change, an increasing global population, economic development and changing consumption patterns, it is expected to further increase with an annual rate of 1.0% (United Nations, 2021). Evaluations of consumption data by the Federal Association of Energy and Water Management (German: Bundesverband der Energie- und Wasserwirtschaft e.V.) have shown that this trend can also be observed in Germany (Bundesverband der Energie- und Wasserwirtschaft, 2022).

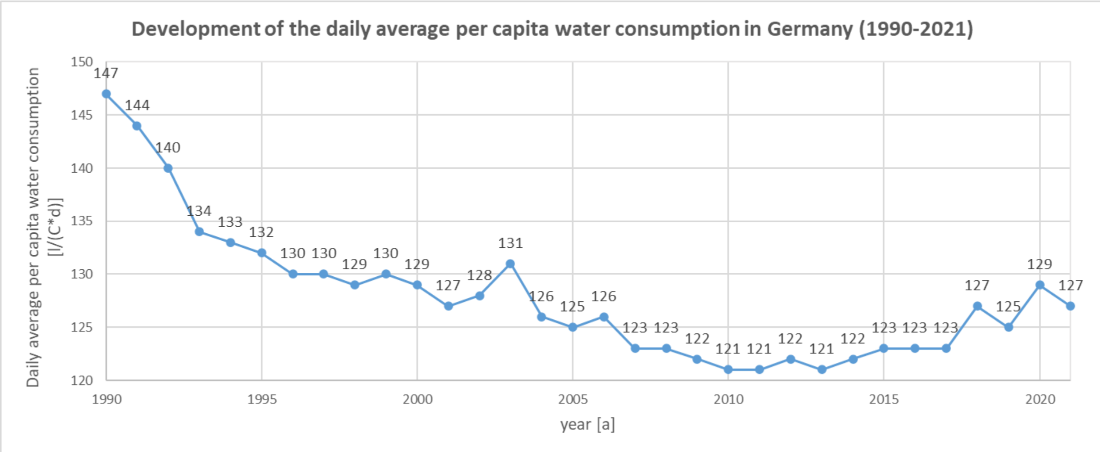


Figure 11 Development of the daily average per capita water consumption in Germany for the period of 1990-2021 based on the figures of Bundesverband der Energie- und Wasserwirtschaft (2022)

Figure 11 shows the development of the daily average per capita water consumption in Germany in the period from 1990 to 2020. Although water consumption has shown a proclivity to fall since the beginning of the 1990s, part driven by the development of water-saving household appliances, which was stimulated by a higher environmental awareness of the consumers and a change in the legislation, a reverse of the trend could be observed in recent years. In addition, an increased water consumption in statistically dry years, e.g., 2003 and 2018, can clearly be detected in Figure 11 (Bundesverband der Energie- und Wasserwirtschaft, 2022).

Water consumption and water demand are influenced by a variety of factors, some of which are summarized in the following list:

- Climate,
- water supply,
- water quality,
- water price,
- economic structure and size of the supply area,
- social structure and type of settlements,
- condition of the supply system and
- sewerage quality and connection degree (Baur et al., 2019).

The water consumption is subject to seasonal fluctuations, which are caused by climatic conditions. Months with high temperatures and low precipitation rates, for example, can lead to an increased water consumption, since, in contrast to the winter months, more water is needed to irrigate lawns or to fill up swimming pools. For this reason, above-average water consumption rates generally occur in the months of May to August, with the lowest water consumption rates being recorded in the months of January and February. Nonetheless, it can be observed that high consumption rates also occur during the winter months. This is especially the case for regions where winter sport tourism is prevalent (Baur et al., 2019). However, even in regions without winter tourism sometimes higher than usual water consumptions can be observed. This phenomenon is often caused by pipe bursts caused by especially harsh weather conditions and their effects, e.g., frost movements in the soil (Data and Statistical Studies Department, 2019). Figure 12 shows an example of the monthly distribution of water consumption of a city, in this case the city of Stuttgart in 2006.

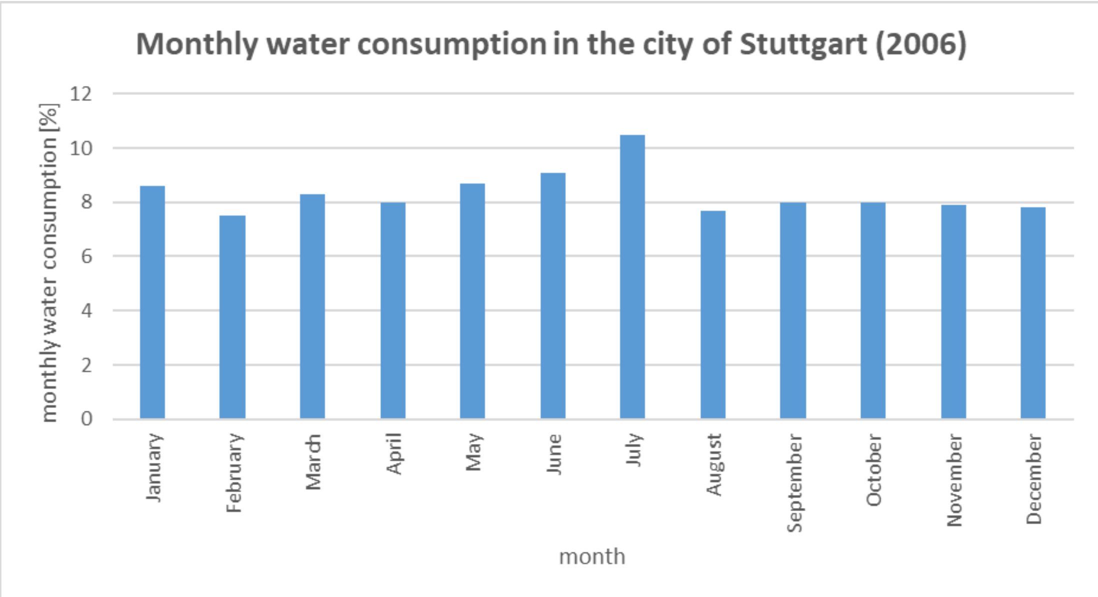


Figure 12 Monthly water consumption in the city of Stuttgart in the year 2006 based on figures from Baur et al. (2019)

In general, the influence of seasonal fluctuations is more pronounced in rural areas, since they have a higher share of gardens and green areas than cities, hence an increased requirement of water for irrigation.

Peak demand

In addition to seasonal fluctuations, water consumption is also subject to daily fluctuations caused by various influencing variables such as habits and human biology (day-night rhythm) (Baur et al., 2019).

According to the W 410 regulation of the German Association of the Gas and Water Industry (German: DVGW Regelwerk W410), the peak daily demand is a planning variable that is decisive for the dimensioning of supply systems and resource capacities and is defined as the highest daily demand in the supply area within an observation period. The future peak demand value is calculated according to the W410 regulations using peak factors, which are determined in dependence to the number of inhabitants (Deutscher Verein des Gas- und Wasserfaches, 2008).

The daily peak factor results from:

$$f_d = \frac{Q_{d,max}}{Q_{d,m}} \tag{1.1}$$

with

f_d: Daily peak factor [-]

$Q_{d,max}$: Peak daily demand [l/(C*d)]

$Q_{d,m}$: Average daily demand [l/(C*d)] (Deutscher Verein des Gas- und Wasserfaches, 2008).

The daily water demand and thus the peak daily demand depend essentially on the size and structure of the supply area. In general, it could be observed that the larger the supply area and the more residents are connected to the supply system, the lower the daily peak factor tends to be. Furthermore, climatic factors, such as the temperature and precipitation rates, have a major impact on the water consumption and thus also on peak daily demand. As already described in the previous chapter, increased temperatures paired with low precipitation rates lead to more water being used for irrigation of green areas and gardens as well as the filling up of pools. This can be observed during statistically dry years, such as 2003 and 2018, where increased peak water consumption could be measured (Baur et al., 2019).

Figure 13 shows an example of the course of the monthly average temperature and the monthly peak daily demand in the city of Stuttgart from September 2006 to August 2007. One can see that the curve of the daily peak factor corresponds to the course of the curve regarding the monthly average temperature, with both reaching their peak in the month of July.

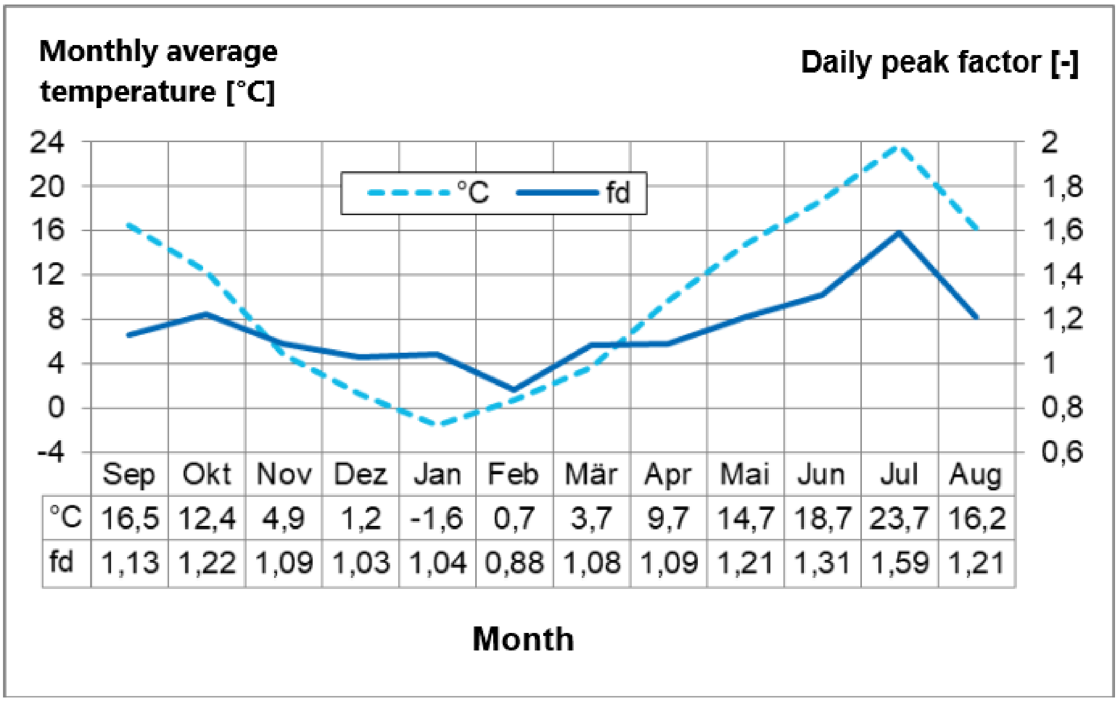


Figure 13 Daily peak factor f_d and monthly average temperature in the city of Stuttgart in the period from September 2006 to August 2007, Source: Baur et al. (2019)

A study which aimed to examine the influence various factors have on water consumption has shown that, in addition to the average daily temperature and the precipitation rates, the duration of dry periods could be identified as a driving factor. Water consumption increases with increasing duration of a dry period. The dependency was particularly evident during the summer months. Figure 14 shows the results of this study. Increasing temperatures and durations of dry periods lead to an increase in water consumption rates, whereas increasing precipitation rates lead to a decrease in water consumption rates (Bundesministerium für Land- und Forstwirtschaft, Umwelt und Wasserwirtschaft, 2012).

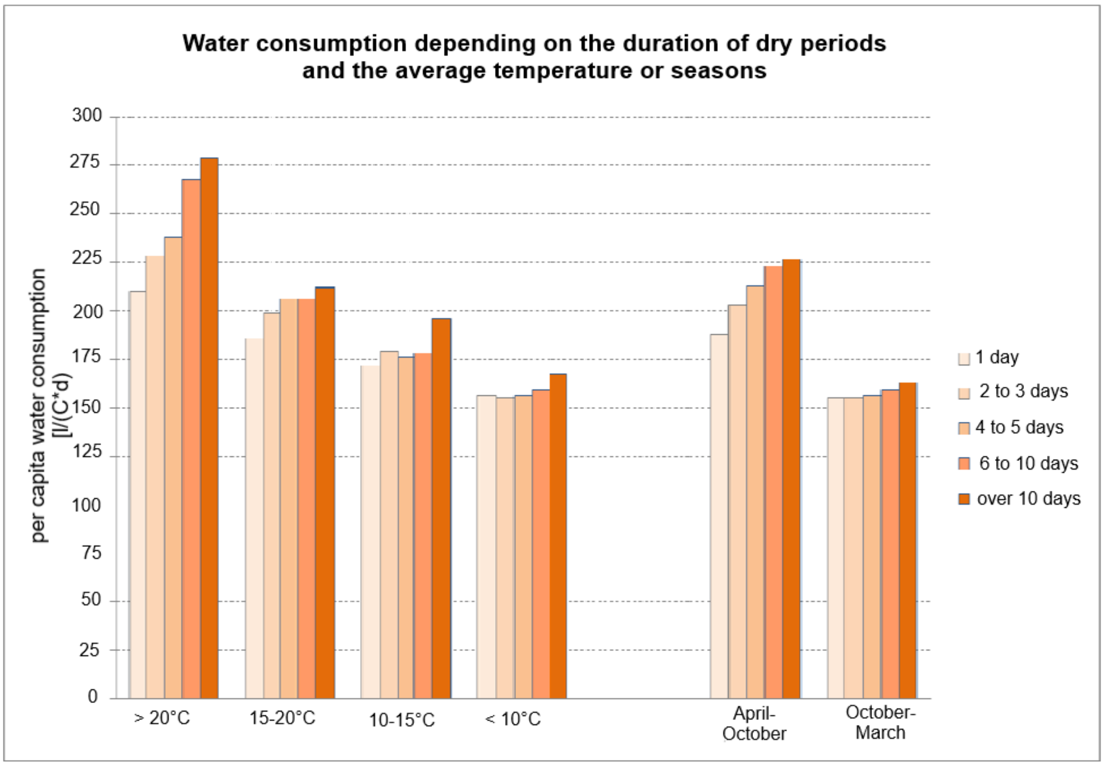


Figure 14 *Per capita water consumption in dependence of the duration of dry periods and the average temperature or season, Source: Bundesministerium für Land- und Forstwirtschaft, Umwelt und Wasserwirtschaft (2012)*

Furthermore, water consumption rates and peak demands are also influenced by the water demand of the commercial and industrial sectors. Whether the water demand of these sectors have a positive or negative impact on the peak water demand depends on whether their water demand is continuous or discontinuous and to what proportion of the overall water demand it accounts for (Baur et al., 2019). Due to the negative effects of climate change, the peak consumption is expected to rise, also resulting in a higher daily peak factor. As a consequence, the gap between the two operation loads, the basic and the peak consumption, will further increase. This must be considered through additional appropriate measures during the planning, construction, and operation of supply networks (Castell-Exner et al., 2010).

Population development

The population development is another important factor that must be considered when assessing the water consumption of a certain area. The influence of the population development on the water consumption can be circumvented, by only considering the per capita water consumption, instead of the overall water consumption. Although the trend in the population development in most of the examined federal states points to a further increase of the population in the future, the results cannot be transferred homogenously to the entire area of the federal states. While the population number in some areas, namely cities and metropolitan areas, is expected to continue to grow, as can be seen in Figure 15, the population number in other areas, namely many rural areas, is expected to decline even further.

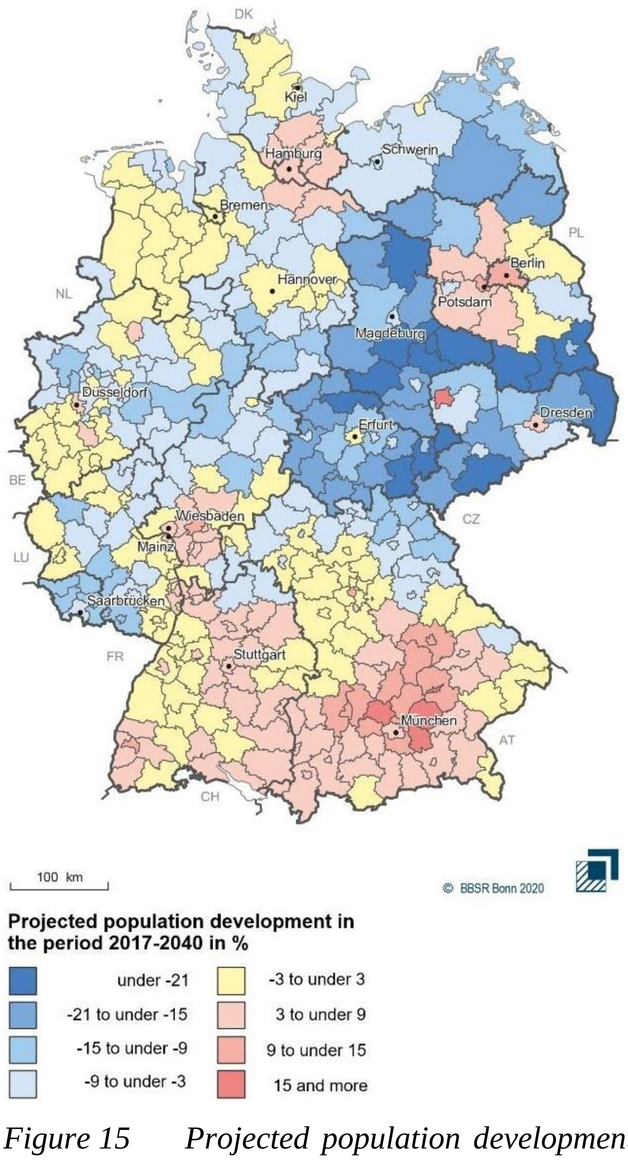


Figure 15 Projected population development in the districts of Germany for the period 2017-2040, Source: Bundesamt für Bauwesen und Raumordnung (2022)

Therefore, when examining water supply systems, the population development of the respective supply area should always be analyzed and taken into consideration. Furthermore, the influence of migration movements due to climate catastrophes and wars, but also technical developments, e.g., remote working, cannot be clearly assessed and therefore cause uncertainty in the assessment of the future population development.

Groundwater renewal rates and spring discharges

Ground water together with spring water and enriched groundwater are of particular importance for the drinking water supply in Germany, as they account for 78.4% of the total drinking water provided (see Chapter 2.1.2). Therefore, an adequate supply of groundwater is essential to guarantee the drinking water provision in Germany. To determine the natural regenerative capacity and the sustainable groundwater abstraction rate of an aquifer, the groundwater recharge rate is commonly determined. Groundwater recharge rates and spring discharges are influenced by a variety of factors, namely the soil condition and its permeability, as well as the precipitation and evaporation rate over a certain region. The groundwater recharge rate is calculated by subtracting the actual evapotranspiration ET_a and the fast runoff component Q_D from the amount of precipitation P. For this purpose, a wide range of mathematical, physical, and chemical methods are available (Petruzzello, 2022).

Due to the available data basis and a lack of reliable data for the real evapotranspiration, a simplified calculation method for the approximation of the potential groundwater recharge (GWR) in the study area, according to the example of Lunkenheimer (1994), was chosen. This leads to the following relationship, according to which the groundwater recharge is equated with the climatic water balance.

$$GWR = WB_{climatic} \tag{1.2}$$

with

GWR: groundwater recharge [mm]

$WB_{climatic}$: climatic water balance [mm] (Lunkenheimer, 1994).

The influences of the surface runoff, the groundwater inflow and outflow and the storage changes in the unsaturated zone are neglected when using this calculation method.

Rising air temperatures as a consequence of global warming, result in higher evapotranspiration rates and thereby less water can contribute to groundwater recharge. The results are declining groundwater formations and falling groundwater levels or spring discharges. Especially in the case of prolonged dry periods, a reduction in the discharge, up to the point where shallow springs dry up, is possible. A study by the Federal Environmental Agency (German: Umweltbundesamt), which was conducted in 2019 and analyzed existing data from 136 groundwater measuring points throughout Germany, concluded that a tendency towards declining groundwater levels and lower spring discharges during the study period of 1971 to 2017, but especially during the last decade, could be observed. When conducting the study, only groundwater measuring points were selected, which cover the uppermost aquifer levels and are as unaffected as possible by human activity, e.g., no relevant groundwater extraction or irrigation taking place in the catchment area or a low degree of soil sealing. This rule out the possibility that the observed changes in the groundwater level are due to parameters other than the temperature and the precipitation (Umweltbundesamt, 2019).

Low water levels in surface waters

The rising air temperatures as a result of climate change and the associated higher evapotranspiration rates and dry periods ensure a higher probability of low water levels in rivers and lakes. Furthermore, declining spring discharges and falling groundwater levels also impact surface water levels (Arbeitskreis Kliwa, 2018).

In the dry years of 2003 and 2015, as well as in 2018 and 2022, low water levels were measured on several rivers and lakes throughout Germany, which restricted both the public and shipping use of the affected waterways. This could also be observed at Lake Constance in 2003 where the water levels fell to its lowest level for a summer month since the beginning of the measurements in 1816 (Ministerium für Umwelt, Klima und Energiewirtschaft Baden-Württemberg et al., 2020).

With a total area of 536 km², Lake Constance is the second largest alpine lake in Europe and one of the main water sources for many cities and towns in the south-western part of Germany. The water level in the lake largely depends on the Alpine catchment area and is subject to seasonal fluctuations. The lowest water levels are measured in winter, since precipitation falling in the catchment area of the lake is bound in the form of snow or ice. During the summer months, the water level reaches its maximum when the snow and ice in the catchment area surrounding the lake melts. The fluctuations in the water level amount to approx. 1.5 m per year. As a result of climate change, air temperatures are expected to increase, leading to precipitation in the winter months falling as rain rather than snow. This leads to a change in the annual discharge regime of the watercourses and to the fact that during summer there is less low-water compensation as a result of the snowmelt and consequently the fluctuation of the water level increases (Landesanstalt für Umwelt Baden-Württemberg, 2013). Figure 16 shows the annual course of the daily mean curve for the periods 1850-1959 (blue), 1960-1989 (green) and 1990-2020 (pink) at the measuring point Constance (German: "Pegel Konstanz").

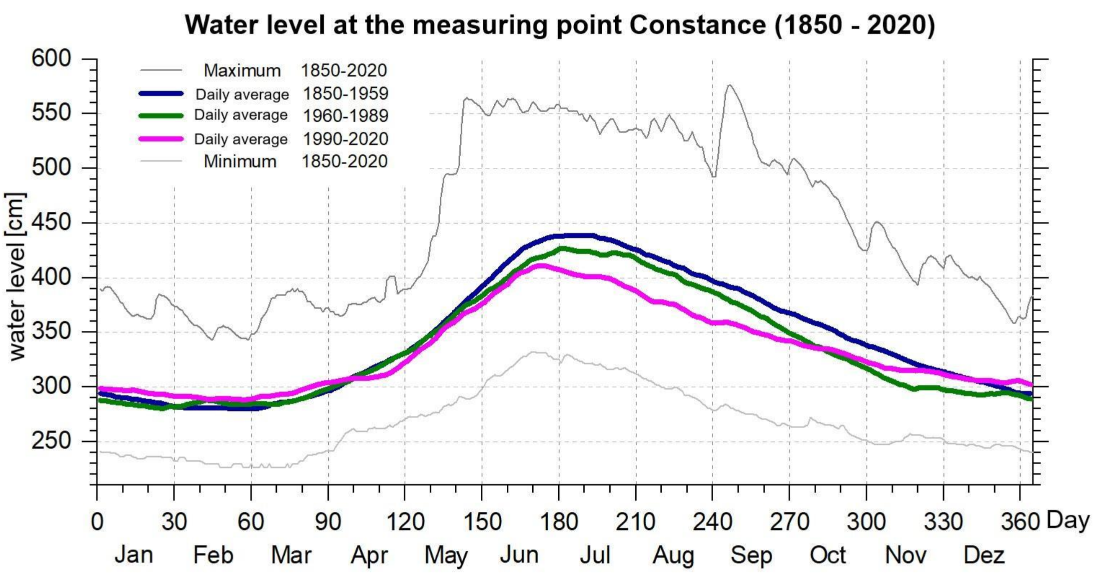


Figure 16 Annual course of the daily mean curve of the water level at the measuring point Constance (Lake Constance) for the periods 1850-1959, 1960-1989 and 1990-2020, Source: Internationale Gewässerschutzkommission für den Bodensee (2022)

A downward trend in mean daily values during the summer months can be observed. Within the measured values shown, the water level during the month of July fell by about 50 cm. Studies show that all high water levels in the lake in the last century occurred up to 1999, while the frequency of low water levels increased from 2000 onwards (Jeromin, 2020). Communities that depend on surface water to maintain their water supply are especially affected by these developments.

2.2.3 Climate models

Forecasts, predictions, and projections play an important part in our society and aid decision-makers in politics, economy as well as administration to make vital decisions, as with the decision to expand production or public facilities due to an expected higher demand in the future. They also play a major role in the public drinking water supply sector, where population development models for example are used to determine the water demand of a supply area in the future. Nowadays, climate models are used for several applications and play an important role in forming and implementing policy decisions as well as informing the public about the potential impacts of climate change (Deutscher Wetterdienst, 2022k).

Weather forecasts

Weather forecasts are a type of climate model, which are used to provide detailed information about the weather over a specific area for the next few hours or the next few days (Deutscher Wetterdienst, 2022l). In order to create weather forecasts, data from different sources are used. These include measuring stations on land and sea, data gathered from planes and weather balloons as well as satellite measurements and imagery. Furthermore, computer models are also used to support the prediction models. Weather forecasts are initialized and mainly influenced based on the observed and currently prevailing climatic conditions. For periods that lie even further in the future (> 10 days), it is not possible to create a precise weather forecast for a specific day, but only to give general trends for the weather of a specific area (Deutscher Wetterdienst, 2022m).

Climate predictions

Climate predictions are a type of climatic model, which reflect a rough trend in climate development over the next few weeks, months, or years. Unlike weather forecasts, climate predictions are not used to predict the weather of a specific area at a specific time in the near future, but rather to predict climatic trends over longer periods of time and over a larger area. These are then used to show deviations from the normal climatic state. In order to create climate predictions, two main data sources are used, one of which is data gathered from observations and measurements, which is similar to the data collected for the creation of weather forecasts. The other data source for the creation of climate predictions are greenhouse gas emission models, which take into account the influence and effects greenhouse gas emissions are expected to have on the climate. Climate predictions are therefore initialized based on the observed and currently prevailing conditions, but further influenced by the long-term developments of greenhouse emission (Deutscher Wetterdienst, 2022k), (Deutscher Wetterdienst, 2022l).

Climate projections

Climate projections are a type of climatic model, which reflect a rough trend in the climatic development over the next few decades (30 – 100 years). Climatic models on this time scale are mainly influenced by the effects of the greenhouse gas emissions and the estimated future scenarios, which depend on global social and political developments (Deutscher Wetterdienst, 2022k). Therefore, in contrast to weather forecasts and climate predictions, the initial state of the atmosphere is not decisive for the creation of climate projections. Rather, climatic projections depend on assumed specifications, so-called climate scenarios. The expected changes in radiation due to the global time course of the concentrations of climate-relevant greenhouse gases, e.g., carbon dioxide or methane, the concentration of aerosol with its influence on the radiation budget and external drivers such as radiative forcing serve as points of reference for the determination of the scenarios. Since all scenarios are merely based on assumptions about the future anthropogenic influence on the greenhouse gas emissions, the selected scenarios and the therefore calculated climatic projections are associated with uncertainties. Therefore, the results of climate projections do not serve as exact forecasts, but rather as a kind of tool with the help of which one can study the effects of different concentrations of greenhouse gasses on the future climate (Deutscher Wetterdienst, 2022k). Based on different scenarios of anthropogenic influence on greenhouse gas emissions a variety of climatic models can be distinguished. The Representative Concentration Pathways (RCPs) are four representative scenarios to which the IPCC currently refers. Intergovernmental Panel on Climate Change (2018) Based on the different trajectory of greenhouse gas and aerosol concentrations, the so-called radiative forcing is calculated, which leads to different climate projections. They serve as the basis for various models of the near and distant future as well as for the development of regional climate models (Deutscher Wetterdienst, 2022n). The most important Representative Concentration Pathways are described below.

Representative Concentration Pathways 2.6 (RCP2.6):

The RCP2.6 is the best-case scenario which is characterized by an improvement of the climatic conditions. It corresponds to a development in which climate protection measures take effect and today's greenhouse gas emissions are greatly reduced. In this scenario, climatic warming does not exceed 2 °C by 2100 when compared to 1860, and radiative forcing begins to decline from 2050 onwards. To achieve this, the maximum value would have to be reached in 2020 and the "zero emissions" status would have to be reached globally before 2080. The RCP2.6 would thus fulfil the agreement of the Paris climate agreement of the UN climate conference. This scenario however is considered to be unlikely.

Representative Concentration Pathways 4.5 and 6.0 (RCP4.5 and RCP6.0):

The RCPs 4.5 and 6.0 represent moderately trending scenarios in which radiative forcing and emission concentrations increase until 2100. After that, either a decreasing radiative forcing takes place or falling emission concentrations are to be expected.

Representative Concentration Pathways 8.5 (RCP8.5):

The RCP8.5 is the business as usual or worst-case scenario and represents a development that runs under the assumption of unchanged high emissions. In this scenario greenhouse gas emissions will continue to increase steadily until 2100, leading to an increase in the global temperature by 4.4 °C in 2100 when compared to 1860.

Furthermore, the radiative forcing will remain high until the year 2300 (Deutscher Wetterdienst, 2022n).

The Representative Concentration Pathways 2.6 is considered as a best-case scenario, while the Representative Concentration Pathways 8.5 is considered as a worst-case scenario. The pathways of both climate scenarios are illustrated in Figure 17.

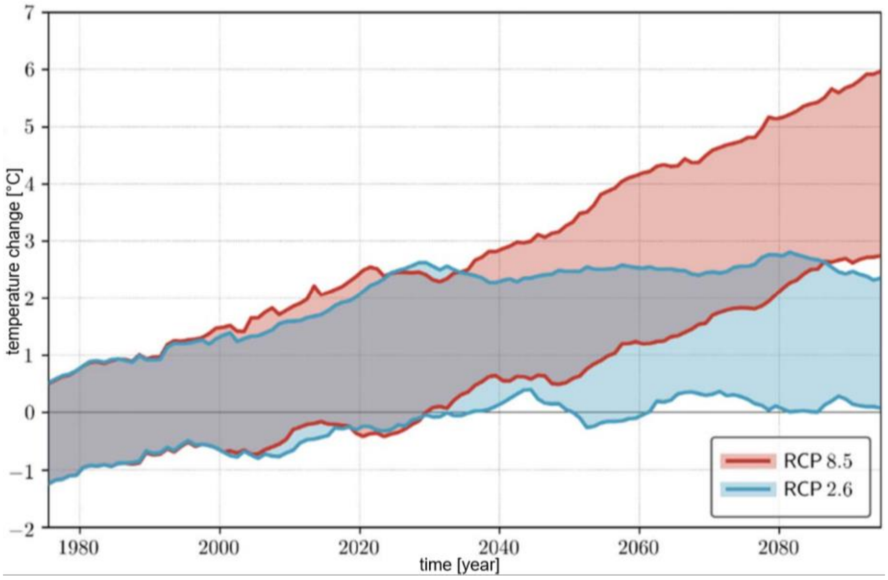


Figure 17 Bandwidth of the time course of the annual mean temperature change in Germany for the scenarios RCP8.5 (red) and RCP2.6 (blue), Source: Schmid (2021)

Comparison between climate projections and measured values

Climate projections from the 1970s and 1980s have been able to reliably predict the current warming trend, as can be seen in Figure 18. The black curve and the thin gray curves show the forecasted mean or the upper and lower range of the forecasted global annual average temperatures. The colored lines show the measured temperature development according to different datasets.

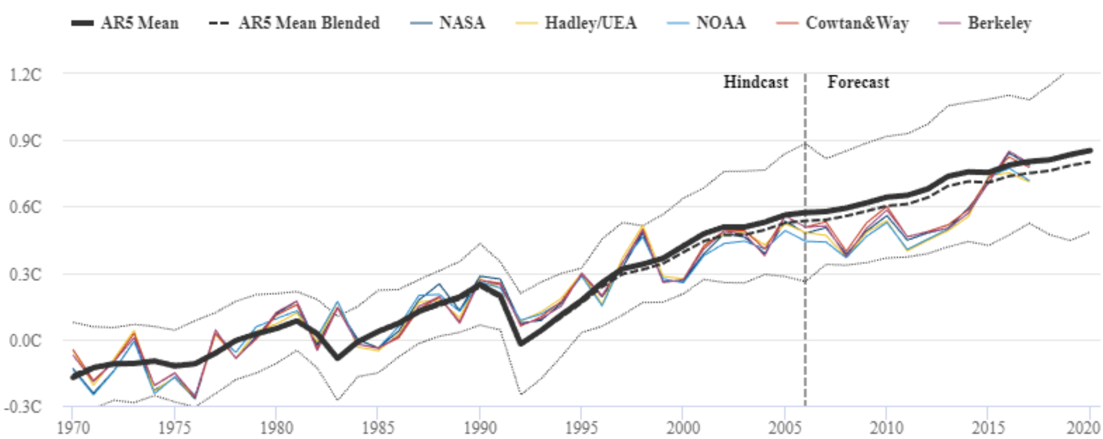


Figure 18 Comparison of climate projections and measured values for the global annual average temperature, Source: Climate Brief (2022)

Figure 18 demonstrates that the measured values correspond to the curves of the predicted data. Therefore, it can be assumed that current climate projections will also be able to predict future climatic developments as precisely or even more precisely, since our understanding of climatic interrelations and the computing power has improved since the 1970s and 1980s (Deutscher Wetterdienst, 2022n).

2.3 Risk analysis of drinking water supply systems

The security of drinking water supply is not only ensured by constantly monitoring, maintaining, repairing, and replacing components of the supply system, but also by the preparedness to react as adequately and as quickly as possible and to restore the normal operation capabilities of the supply system after hazards and associated system failures in the freshwater supply network have occured. To achieve this, it is necessary to conduct a risk analysis of the total water supply system. The aim of a risk analysis is to assess whether a water supply system is able to provide drinking water in the face of hazards and hazardous events (Verband kommunaler Unternehmen, 2019). In addition, its aim is to find out which system components are particularly susceptible to certain hazardous events and which steps must be taken to rectify the damages that have occurred during or in the aftermath of a hazardous event. Once the hazards and hazardous events have been identified, they should be used to carry out a risk assessment for the system in question, with the help of which countermeasures and damage minimization measures can be developed and implemented. Finally, a validation of the decided on and implemented countermeasures should be carried out in order to identify possible weak points. This process should be reviewed periodically so that the risk analysis includes all new significant developments and insights and thus keeps the water utility company prepared in case of a hazard or hazardous event (Wienand et al., 2019).

The goals pursued by the risk analysis of drinking water supply systems can be divided into the following three categories:

- The identification of relevant risk scenarios for the supply system (risk identification),
- the determination of the extent of damage and the likelihood of occurrence of the relevant risk scenarios (risk assessment) and
- the comparison of risks and the creation and implementation of countermeasures (risk management) (Wienand et al., 2019).

The prescribed procedure for the risk analysis of a drinking water supply system is illustrated in the figure below.

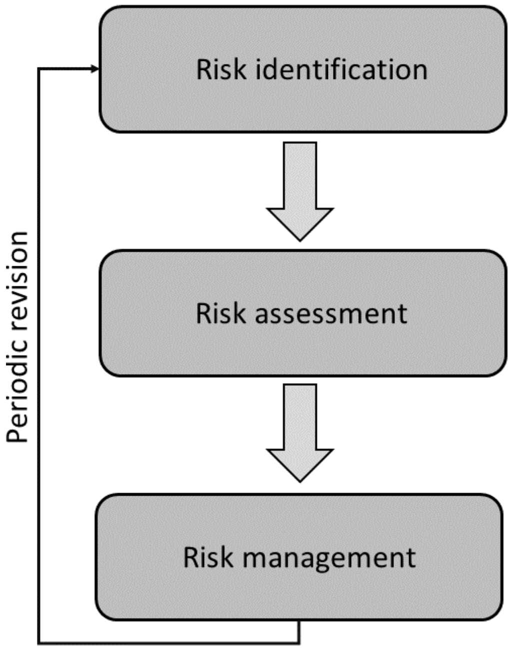


Figure 19 Flowchart of the prescribed procedure for conducting a risk analysis of a drinking water supply system based on Deutscher Verein des Gas- und Wasserfaches (2008)

2.3.1 Risk identification of/for drinking water supply systems

Hazards and hazardous events

Hazards and hazardous events can never be completely controlled. Although modern technology empowers us to build technical structures, which provide a certain level of protection, they are nevertheless only designed to withstand and provide protection against an event with a defined return period, since they are limited by various factors such as the financial means available or due to limitations in the material properties being used and therefore cannot guarantee protection against every possible scenario (Bundesministerium des Inneren, 2009).

Description of drinking water supply systems

The description of the current state of the drinking water supply system is the basis for the development of a risk analysis. It should be conducted in consideration of all legal provisions and technical regulations and should include the following elements:

- Summary overviews,
- system specifics,
- network development strategies and
- further information (e.g., reliability considerations of risk-relevant components).

Thereby the description of the supply system should begin and end at the transfer points and include all steps from the catchment area to the handover point to the customer (Deutscher Verein des Gas- und Wasserfaches, 2008), (Deutscher Verein des Gas- und Wasserfaches, 2011). In addition, foreseeable developments and future plans, including the population development and the expansion of the supply network, should be included in the description of the drinking water supply system. Since every water utility company is structured differently and has its own special features that are adapted to the individual conditions on site, the description of the drinking water supply system must be made individually (Deutscher Verein des Gas- und Wasserfaches, 2011).

Risk identification

The aim of the risk identification in regard to drinking water supply systems is to identify hazards and hazardous events, which have the potential to disrupt the normal operation of the water supply network, and to determine conceivable conditions and events that could lead to the occurrence of a hazard (Deutscher Verein des Gas- und Wasserfaches, 2008). It should be ensured that the risk identification includes all steps that are crucial for the normal operation of the supply, ranging from the catchment area to the handover point to the customer, and investigates how these process steps can potentially be impacted by hazards and hazardous events (Wienand network et al., 2019).

The following list contains an overview of possible process steps that should be taken into consideration when conducting a risk identification:

- Raw water catchment areas,
- water production plants,
- raw water transport,
- water treatment,
- drinking water transport,
- water pumping systems,
- water storage facilities,
- water meter shafts, pressure reducer shafts, pipe rupture protection shafts and transfer shafts and
- water distribution (supply areas) (Wienand et al., 2019).

Since every water utility company is structured differently and has its own special features that are adapted to the individual conditions on site, the risk identification should be carried out individually for each supply system (Deutscher Verein des Gas- und Wasserfaches, 2008). Many water suppliers have been in operation for a long time and can draw on a wealth of experiences regarding hazards and hazardous events. That being the case, when performing a risk identification, one should first consider hazards and hazardous events that have occurred in the past and that have impacted the drinking water supply, since they can offer valuable information about possible weak points in and limitations of the supply system. Furthermore, they offer valuable insights on the emergency reaction capabilities of the water utility company (Wienand et al., 2019). Risk control measures (Chapter 2.3.3) that have already been taken to address hazards and hazardous events can deliberately be disregarded when conducting a risk identification. This enables the risk identification to be carried out regardless of the effectiveness of the measures already taken. After collecting the data in regard to past hazards and hazardous events, the remaining potential risks to the water supply system can be gathered. One should not simply focus on the potential risks hazards and hazardous events pose, but likewise on the possible negative effects these can have on the drinking water supply. These negative effects should be listed and described briefly (Deutscher Verein des Gas- und Wasserfaches, 2008).

2.3.2 Risk assessment of drinking water supply systems

Once the potential risks and dangers for the drinking water supply system have been identified, a risk assessment for the supply system in question can be carried out, with the help of which in a next step risk control measures can be developed. According to the technical code "Safety in the drinking water supply - Risk management during normal operation" from the German Association for Gas and Water from 2008, a risk is defined as the product of the likelihood of occurrence and the extent of damage of a hazard or hazardous event (Deutscher Verein des Gas- und Wasserfaches, 2008). The values of the likelihood of occurrence and the extent of damage of a hazard or hazardous event must therefore be determined before the risk assessment of the drinking water supply system can be carried out.

Likelihood of occurrence

The likelihood of occurrence of a hazard or hazardous event is determined by calculating the annuity of a specific hazard or hazardous event. Various mathematical models as well as calculation and modeling software can be used for this purpose (Wienand et al., 2019).

Extent of damage

The extent of damage is directly correlated with the duration of the hazard or hazardous event and the duration of its impacts. The longer the hazard or the hazardous event and its impacts prevail, the more consumers are potentially affected by a lack of access to fresh and clean drinking water (Wienand et al., 2019). Water storage tanks are designed to even out daily fluctuations and the water stored in them is on average sufficient to supply drinking water for 12 to 24 hours. Short or medium-term hazards, that fall within the time frame of maximum 12 to 24 hours and do not have a direct impact on the distribution network, can be covered by storage tanks. Elevated storage tanks alone, however, are therefore not sufficient to ensure an adequate drinking water provision in case of a hazardous scenario of a longer extent. Taking that into account, one also needs to examine whether the affected water utility company is connected to other water suppliers who can help to maintain the drinking water supply. If that is not the case, the drinking water supply in the affected supply network is as interrupted. If, on the other hand, an external supply is available, it must be determined whether the supply of the whole or just a certain proportion of the population (e.g., only certain supply zones) can be guaranteed. In the case that the provision of drinking water is possible for at least an individual proportion of the population, it can be assumed that the supply can be maintained partially. Furthermore, even if one or more working external possibilities to supply water supply exist, the vulnerability of the other components of the drinking water supply must also be checked. If the elevated storage tanks or pumping stations are highly vulnerable (i.e., the functionality is not given), the drinking water supply cannot be maintained despite an existing external water supply (Wienand et al., 2019).

2.3.3 Risk management of drinking water supply systems

For hazards and hazardous events for which a need for action has been derived in the scope of the risk assessment, risk control measures must be developed and implemented, in order to ensure that the drinking water provision can be met at all times. As described in Chapter 2.3.2, the risk emanating from a hazard or hazardous events is defined as likelihood of occurrence and the extent of damage of a hazard or hazardous event. Since the likelihood of occurrence cannot be influenced, the only possibility to minimize the impact of a risk is through a reduction of the extent of damage. During the selection processes, preference should be given to measures with a high process reliability and operational stability (Deutscher Verein des Gas- und Wasserfaches, 2008).

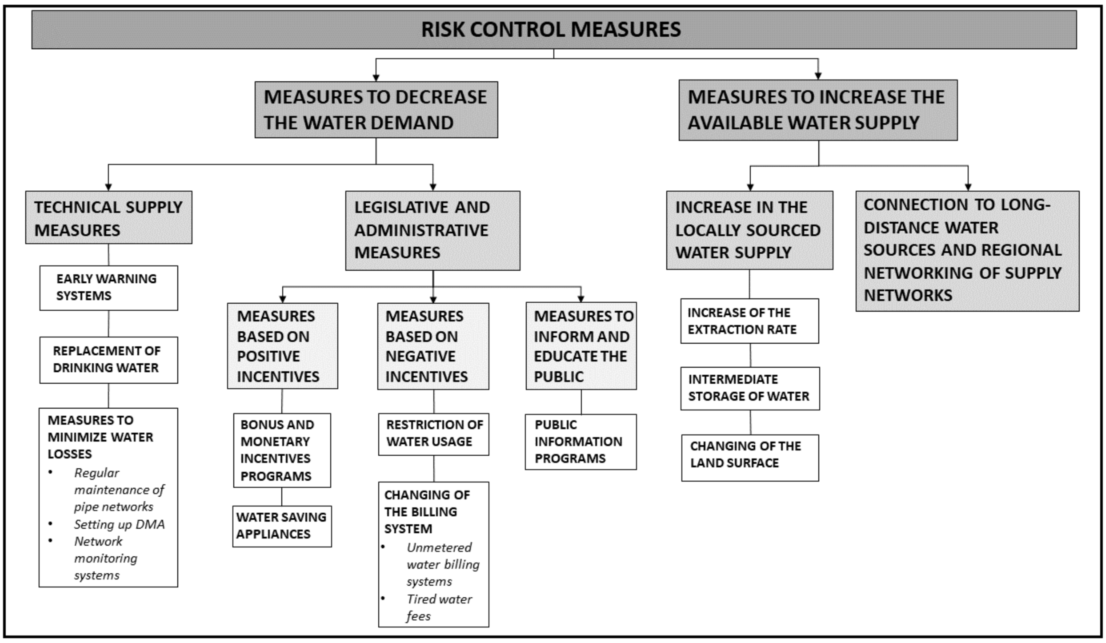


Figure 20 Overview and classification of the risk control measures in connection with the impacts of climate change on the water demand

As mentioned in Chapter 2.3.2, climate change poses a threat if changes of the climatic conditions lead to the future water demand exceeding the future available water supply. Therefore, in general, one can distinguish two types of measures. On the one hand, measures which aim to reduce the drinking water demand and on the other hand, measures which aim to increase the drinking water supply. Figure 20, which is based on …, provides an overview and classification of the measures identified in connection with the impacts of climate change on the water demand.

2.3.3.1 Measures to decrease the water demand

If the water supply cannot be increased, measures that aim to decrease the water demand are the only way to counteract an increasing water demand. Depending on influencing factors such as the condition of the supply network, the political will of the decision-makers as well as the behavior and habits of the consumers, a different savings potential for each water utility company exists. In general, it can be observed that the domestic and small business consumption has the greatest savings potential, as this sector has the largest share of the overall drinking water consumption, as can be seen in Figure 2.

Legislative and administrative measures

Legislative and administrative measures to reduce water consumption do not intervene directly into the supply system, for example by replacing the supply lines, but rather intend to reduce the water consumption by influencing consumer behavior. The legislative and administrative measures can be divided into three groups, namely measures based on positive incentives, measures based on negative incentives and measures to inform and educate the public, as can be seen in Figure 20. In order to influence the water consumption of consumers, measures based on positive incentives offer some kind of advantage for the consumer, e.g., by establishing and utilizing reward systems, which reward water conservation efforts or offer incentives to implement water conservation systems. Measures based on negative incentives, on the other hand, exert an influence on the water consumption of consumer groups by penalizing excessive water use, for example through the enforcement of restrictions or tiered water fees. Measures which aim to inform the public focus on the provision of information on the current and prospective state of the local water resources, while in addition offering practicable advice on how water can be saved.

Bonus and monetary incentive programs

An example of measures based on positive incentives are the bonus and incentive programs for water conservation that are currently brought forward by Thames Water Utilities Limited. Thames Water is the UK's largest water supplier, supplying 2.6 million m^3 of drinking water per day to a total of 9 million consumers in Greater London (Thames Water, 2022a). The utility company is faced with the challenge that the number of residents is constantly increasing due to migration movements. According to the Office for National Statistics, the population is expected to increase by 2.7 million by 2050 (Thames Water, 2022b). This poses a major challenge for the security of the water supply. For this reason, the company offers various programs with the aim to reduce the water consumption. Consumers that have a smart meter installed can, for example, register for a bonus program. With the data collected from the smart meters participants can track their weekly water usage rates and are provided with a summary report. In addition, information material with advice on how to reduce water consumption in the household is offered. Households that manage to minimize their water consumption collect points, which they can redeem prizes with, such as gift cards (Thames Water, 2022c). Another program that is offered is the incentive program for housing developers. Housing developers who develop new properties which achieve “water neutrality” by equipping them with low water using devices and rainwater collection systems, receive a discount on the charges for connection to the public drinking water network (Thames Water, 2022d). It is conceivable that similar programs are transferable to sectors that have a high water consumption, such as car washes or food production companies.

Water saving appliances

Victoria is the most densely populated federal state in Australia and repeatedly struggles with water supply shortages. Driven by these circumstances, many water utility companies were looking for innovative ways to reduce the overall water consumption, one of which led to the creation of the so-called showerhead exchange program. Many of the older shower head models, which are still in use today, were not designed to save water and thus a lot of water is consumed unnecessarily. For this reason, the water suppliers offered their consumers water-saving shower heads for free. By replacing an old shower head that uses 12 liters per minute by a new model that only uses 8 liters per minute, one can save up to 1/3 of the water used while showering (City West Water, 2021). The program offers consumers a double monetary advantage. On the one hand, they do not have to buy a new shower head and on the other hand, the shower heads lower their water consumption, which has a positive effect on their water bills. Many water utility companies accept the fact that the implementation of such a program leads to increased costs, since they hope that the program will reduce the overall water demand and there will be no need for the development of new water sources, especially since the development of new water sources often is not possible at all or cost many times more than the program. Similar programs have also been implemented in other cities and regions struggling with water shortages, such as Istanbul, where non-profit organizations hand out water-saving appliances for free (Tansel, 2021).

Restriction of water usage

The irrigation of gardens and green spaces are one of the main water consumers during particularly arid periods. Above all, spray irrigation during the hottest hours of the day is particularly wasteful, since the water losses with this form of irrigation are particularly high, adding up to around 50% in some cases. Therefore, many cities and communities suffering from water shortages have implemented restrictions on the water usage in order to save water and to manage the water sources as ecologically as possible. Such restrictions, for example, include bans on watering of gardens and green spaces, the filling up of ponds and pools, the washing of hard surfaces, such as driveways and streets, and the washing of vehicles (Las Vegas Valley Water District, 2022a), (California Water Boards, 2022). For this purpose, a legal basis must be created by the responsible legislative authorities. In some supply areas, an executive authority has been developed specifically to monitor the compliance with the prohibitions, one of which is the so-called Water Patrol, which was established by the water utility company Las Vegas Valley Water District. Residents who are caught having violated the restrictions set in place must expect fines, so-called water waste fees, which start at $80 and can go up to $5,120 (Las Vegas Valley Water District, 2022b).

Changes in the billing system

There are several possible rate structures for billing drinking water consumption, some of which are of historical origin and offer little or no incentive to use water sparingly. One of the most common ways of billing drinking water today is via a so-called uniform rate, where a fixed sum is paid for a specific amount of water, but there are also other billing systems which are described in the following paragraphs (Alliance for Water Efficiency, 2022a).

Unmetered water billing systems

In most parts of Europe, nowadays, it is common for water consumption to be determined by water meters. In some places, however, water consumption is not measured and is instead billed by using so-called unmetered water billing systems. Since the water consumption is not being determined, fixed installments are paid for the water usage. As a result, consumers do not have an incentive to reduce their water consumption, but on the contrary, they have an incentive to claim as much water as possible for themselves. Therefore, if possible, a system change should take place and water meters should be installed. This has not only shown to raise the value of the commodity water in the minds of the consumers and to reduce the overall water consumption, but also has the advantage that it provides a better basis for network calculations and simulations, since water consumption can be assigned more precisely (Thames Water, 2022e).

Tiered water fees

In a drinking water supply network where the water consumption is registered with water meters, one has the option of implementing alternative water rate structures. In contrast to the uniform rate structure, alternative rate structures are designed specifically to encourage water conservation. One such billing system is the water budget-based rating system, which sets up individualized water budgets for each consumer. Based on specific factors and characteristics, such as the number of persons per household, the evapotranspiration rate, or the plot size, an individual and reasonable water budget is determined for each household. As long as the water consumption of a household is within the limits of its individual water budget, a low water price is paid for the water consumed. However, as soon as the water consumption exceeds the limit of their water budget, water prices rise sharply. This billing system was pioneered in the 1990s in California and has since been successfully implemented by many water suppliers across the USA (Alliance for Water Efficiency, 2022b). Studies have shown that water budget rate structures have reduced the overall consumption substantially. The water consumption in the Californian city of San Juan Capistrano, for example, declined by 35% when comparing the periods before and after the implementation of the water budget rate structure (Mayer, 2008).

Public information programs

A measure to counteract the forecasted trends regarding climate change and its effects on the water supply is to involve the public. Through various media outlets, events and school lessons, the population can be made aware of the importance of water and of the urgency to change one's consumption behavior in an effort to conserve water. An economical use of drinking water together with the transition to other water resources can help to reduce the per capita consumption and thus relieve pressure off of the drinking water resources. Furthermore, informing the population about times of peak consumption and their impacts on the supply system can help to decrease the pressure on the supply network. In the early 2000s, Australia experienced one of the worst droughts recorded in its history, which affected large parts of Southern Australia and lasted for several years. Public awareness programs have been implemented successfully in the city of Melbourne to help raise the awareness of the public to the dire situation of the water reservoirs that are used to supply the city with drinking water.

For this purpose, the utility company Melbourne Water set up electronic billboards indicating the current capacity of the reservoirs in exposed places throughout the city. In addition, other media outlets, such as newspapers and television, also drew attention to the current situation of the water supply. Together with other measures, the public information program has led to a reduction of the overall water consumption, which consequently held up the occurrence of “Day Zero”, the day on which the water supply can no longer be provided (Climate Access, 2014).

Technical supply measures

Technical supply measures aim to reduce water consumption directly by intervening into the supply system, for example by replacing leaking supply lines. Most of the technical supply measures can be implemented directly by the water supplier itself and therefore have the advantage that they do not require the involvement and approval of third parties.

Early warning systems

Early warning systems are critical components for the adaptation to climate change and with the objective of avoiding or reducing the damage caused by hazards and hazardous events. In order to be efficient, early warning systems need to actively inform the target group affected by efficiently broadcasting messages and warnings (Climate Adapt, 2019). One example of such an early warning system in Germany are the applications Nina, of the Federal Office of Civil Protection and Disaster Assistance (German: Bundesamt für Bevölkerungsschutz und Katastrophenhilfe) or Katwarn, of the Fraunhofer Institute, which both warn the population of disasters and hazards through notifications on the application (Bundesamt für Bevölkerungsschutz und Katastrophenhilfe, 2022). Early warning systems also exist in the hydrological sector. An example is the U.S. Drought Monitor, which provides a weekly map of drought conditions for the United States that is used by the U.S. Department of Agriculture and the Federal Emergency Management Agency, among others, to evaluate which areas may need financial assistance due to losses caused by droughts. For this purpose, they use the imagery of the GRACE and GRACE-FO (Geosciences’s Gravity Recovery and Climate Experiment - Follow On) satellites, a joint project of NASA and German Research Center for Geosciences, as well as meteorological forecasts. The forecast provided by the U.S. Drought Monitor extend over the next 30 to 90 days (National Drought Mitigation Center, 2022).

Replacement of drinking water

Figure 4, which displays the domestic drinking water usage by usage type, clearly demonstrates that drinking water is used for applications for which water of lower quality would suffice. According to Paragraph §3 of the Drinking Water Ordinance, only approximately 60% of the water used in German households is defined as drinking water and as such is subjected to drinking water standards, which includes water used for drinking and the preparation of meals, for dishwashing and personal hygiene as well as water used to wash the laundry. Water that is used to flush the toilet or to irrigate gardens does not have to exhibit the same qualitative requirements as water intended for human contact and consumption. The same also applies to many applications and processes in the industry (Bundesministerium der Justiz, 2021). The drinking water usage of these applications and processes could be replaced by graywater, rainwater or service water and would help to decrease the pressure on the drinking water resources. By switching to other water sources, toilet flushing alone could reduce the drinking water consumption in Germany by nearly one third. Implemented on a nationwide scale, this would mean that the national average per capita consumption would decrease from 123 to 90 l/(C*d). In order to implement these measures, many structural changes would be necessary, including the retrofit of plumbing in houses and buildings, the construction of rainwater collection and storage facilities or the installation of a service water pipe system. These changes are easier to implement in rural areas and new buildings, because more space is available and the differences in the plumbing can be integrated during the planning stage (Freeflush Water Management, 2022).

Measures to minimize water losses

Water losses in the system occur when water is used without being assigned to a consumer and without fees being charged for its consumption. This includes water that seeps into the ground due to leaks in the pipe network or in storage tanks, measurement errors caused by inaccurate water meters, but also illegal water withdrawals from hydrants or illegal connections to the network. The therefrom resulting costs are redistributed to all consumers via the water price (Bayerisches Landesamt für Umwelt, 2019). Although water losses cannot be completely avoided, efforts should be made to reduce them to a minimum in order to conserve the resources, but also to protect the consumers' financial means.

<u>Regular maintenance and repair of pipe networks</u>

In order to increase the technical service life of pipes, they must always be maintained and repaired. With an annual renewal rate of 1%, it takes 100 years to completely replace all pipes from the supply system. A study conducted by various associations and authorities from Baden-Württemberg concluded that water supply companies from this federal state revealed that the network renewal rate in the year 2020 was 0.5% on average, which means that the renewal cycle lasts 200 years (Rödl und Partner, 2022). Similar values can also be observed for the other federal states of Germany (Rödl und Partner, 2019). In order to maintain the condition of the supply network, a renewal rate of at least 1.5 to 2.0% should be aimed for. The reactive maintenance approach of many water utility companies leads to a deterioration of the supply network and high prospective costs for future generations (Rödl und Partner, 2022). In addition to the regular maintenance and repair of structural components, it is advisable to carry out structural reports and pipe network calculations to have the supply network properly assessed and to identify possible weak points and deficits.

<u>Setting up of district metered areas (DMA)</u>

Another way to minimize water loss is by implementing so-called district metering areas or DMAs. To achieve this, in a first step, the entire coverage area is divided into smaller coverage units. Existing supply zones are suitable for the creation of DMAs, as long as they are not too vast and supplied from a single supply line. In a next step, water meters are being installed at the feed-in points of the DMAs, which enables one to balance each of the metered areas individually. This means that the water losses can now be assigned to a smaller area, which consequently helps localize the water losses in the system faster and more efficiently (DTK Hydronet, 2019).

Network monitoring systems

A further method to minimize water losses in supply systems is through network monitoring. For this purpose, flow measurement devices are attached to the outside of water pipes at hydraulically relevant points. These are then used to permanently measure the volumetric flow rate inside the pipe. If the measuring devices register changes in the flow behavior, such as when a pipe bursts, the system alerts the network operator and facilitates leak detection by calculating and indicating an area in which the leakage is suspected to have occurred. In order to minimize the water losses through such a system, the detection by the monitoring system should be complemented by a rapid intervention and repair of the damaged utility (RBS wave GmbH, 2015).

2.3.3.2 Measures to increase the available water supply

The second set of measures, which can be implemented to counteract the negative effects of climate change on the drinking water demand, aim to increase the available water supply. There are mainly two ways to do this, one of which is to increase the locally sourced water supply sources and the other one is the purchase of drinking water from long-distance water utility companies. Depending on influencing factors such as the hydrogeological composition of the subsoil there exists a different potential for each water utility company.

Increase in the locally sourced water supply

Increase of the extraction rate

One way to increase the supply capacity is to tap into already existing or new locally available water sources and thereby increasing the overall extraction rate. This can be achieved by drilling new wells or by developing springs for the use of drinking water. To do this, it must first be examined which yield can be expected from the local groundwater resources and whether it can cover the required demand. If such examinations have not been conducted yet, test drilling and pumping tests need to be carried out. In addition, it must be clarified with the responsible authorities whether a permit for increased extraction can be obtained. When designing the new wells and springs, it is important to anticipate a decrease in future water resources due to climate change. Past hot summers have already caused a temporary decrease of the yield of surface wells and springs (Karger et al., 2008). Apart from the above-mentioned possibilities, other water resources can also be utilized to supply drinking water or to replace applications where drinking water is currently used, but lower quality water would suffice (see Chapter 2.3.3.1). One possibility is to reuse water, for instance through the usage of treated wastewater for the irrigation of urban vegetation or the flushing of sewers. Another possibility would be the desalination of saltwater.

Change in land surface

Soil sealing leads to precipitation no longer being able to seep through the soil into deeper layers of the earth and thus hinders it from contributing to the formation of new groundwater. Instead, the precipitation is drained off on top of sealed surfaces and is diverted to the nearest body of water, where it favors the occurrence of a flood event taking place during heavy rain events. Although soil sealing in Germany has shown a downward trajectory in recent years, still 56 ha of undeveloped land are converted into areas for settlements and traffic every day, of which 45.1% are being sealed. This leads to the surface sealing of 25.3 ha of land in Germany every day (Umweltbundesamt, 2022). One way to counteract the process is to unseal already sealed areas or to minimize the degree of sealing in new construction projects. Although this method would only have a limited local impact in the catchment areas of the wells and springs in the study area of Southern Germany, since most of the time they are already located in highly permeable areas, such as forests or fields, it would have an impact on the groundwater resources on a global level. The unsealing of urban areas would mean that more rainwater would seep through the soil, increasing groundwater renewal rates and consequently leading to the rise of groundwater levels. As a result, trees in cities would not have to be watered at all or only much later than usual during dry spells or summer months with little precipitation.

Intermediate storage of water

As described in Chapter 2.2.2, water consumption in Germany is seasonally dependent. It can be observed that cold periods exhibit lower water demands than hot periods. If possible, it is therefore advisable to utilize the excess water that is available during rainy months with low water demands by storing it in order to be able to access it during months with high water demands. Based on the storage type used one can distinguish between above ground and in the ground storage facilities (Thomas et al., 2011). One way to store excess water above ground is through the creation of freshwater reservoirs. This can be accomplished by the erection of barrages in streams, which hold back excess water during periods with increased runoff, or by the creation of stormwater fed reservoirs, which for example divert excess precipitation away from urban zones into the reservoirs. One such structre is the Marina Barrage, which is located in Singapore and separates the freshwater reservoir Marina Reservoir from the Straits of Singapore. The reservoir is fed by several rivers, whose catchment areas are heavily urbanized and stretch out over 10.000 ha, covering approximately 10% of the city-states water demand (Singapore's National Water Agency, 2022). Another major project that aims to store surplus stormwater and is still in the planning phase is the Rory M. Shaw Wetlands Park Project, located in Los Angeles County. For this purpose, 21 ha of a 46-hectare area is to be converted into a detention pond, where stormwater will be collected, while the remaining area will be divided into a part that will be turned into a wetland and be used for the treatment of the stormwater and another part which will be used as a recreational area. After the treatment the stormwater will be pumped to existing infiltration basins, which are operated by a group of Los Angeles Departments (Los Angeles County, 2022).

<u>Connection to long-distance water sources and regional networking of supply networks</u>

In the event that the water demand cannot be met, and the locally available water resources are exhausted, there is the possibility of obtaining water from other water utility companies, which have capacity reserves. For this, it must be checked whether a water supplier in the near vicinity meets the criteria or whether the pipes of a long-distance water supplier with capacity reserves runs through or near the own supply area, to which one could establish a connection. However, one should note that many long-distance water suppliers, such as the Bodensee Wasserversorgung, have already reached their capacity limits and are therefore unable to deliver more water or to enter into contracts with new customers (Gajer, 2022). Therefore, this option should only be considered, when all other options have been exhausted or in the case that they are economically unviable.

2.3.4 Periodic revision of the risk analysis

After all hazards and hazardous events as well as their likelihood and extent have been determined and the appropriate measures have been developed and implemented, a periodic review should be carried out (Wienand et al., 2019). Infrastructure, such as drinking water supply systems, constantly needs to be repaired and maintained in order to guarantee their functionality, but also needs to be adapted to changing circumstances and conditions, such as population development, changing consumer habits, climate change and the connection of new districts. The risk analysis, assessment and management of drinking water supply systems should therefore be carried out at regular intervals, with the objective to always stay up to date and to include new findings and changed data bases. It is recommended to repeat the risk analysis at intervals of 3-5 years or when major changes to the supply system are imminent (Deutscher Verein des Gas- und Wasserfaches, 2008).

2.4 The use of machine learning for the prediction of the future water demand

Machine learning can be defined as a collection of methods and techniques, with the help of which data patterns can be detected automatically, which in turn can then be utilized for the prediction of datasets or data points, which have not been observed. It offers a wide range of possible applications in different sectors and is used, for example, in face or voice detection and recognition, in the optimization of processes or for the prediction of stock market prices. In general, one can distinguish two approaches of machine learning, the descriptive or unsupervised learning approach and the predictive or supervised learning approach. The predictive or supervised learning approach can further be divided into two categories according to the type of the output or response variables. If the output values are considered to be categorical or nominal variables they belong to the category of classification or pattern recognition, while output values which are considered to be real-valued variables belong to the category of regression (Murphy, 2012).

Many successful investigations and studies in the field of machine learning based water demand forecasting, which falls into the category of time series forecasting, have led to its establishment as an innovative approach within the framework of water demand development. Depending on the framework of the conducted studies as well as the available data basis, various influencing factors can be incorporated into the simulations, such as economic, demographic or climatic factors. To date, climate-based simulations in the field of water demand development have been limited to short- or medium-term forecasts, i.e., to a time frame of a few hours to several months. For this purpose, in addition to historical climatic and water supply-specific data, data from weather forecasts or weather prognoses were used as the data basis for the simulations (Ghiassi et al., 2008).

The obtained information and results regarding the analysis and forecasting of the future water demand, are of great importance since they enable an optimal supply demand management and serve as the basis for the early implementation of measures that can assist in meeting the water demand, such as increasing the treatment capacity, provided that further production, treatment, and storage capacities are available (Vijayalaksmi et al., 2015).

Nevertheless, the operational flexibility of water supply systems is only given to a certain degree as they are designed for a long service life, spanning over several decades, and their construction, maintenance and expansion require considerable investments.

Due to the restricted operational flexibility of the water supply systems, decisions should be made at an early stage with regard to possible measures to ensure that the water demand can continue to be met at all times in the future. Consequently, this implies that to realize this, long-term predictions of the future water demand, which span over the next few decades, are required. Long-term forecasts in the area of water demand development have also been conducted, but these have been limited exclusively to the effects of economic and demographic factors on the future water demand (Nawaz et al., 2019).

In this process, non-linear models such as artificial neural networks have proven to be particularly suitable since, in contrast to linear models such as multivariate linear regression (MLR) or autoregressive integrated moving averages (ARIMA), they can represent the actual water consumption, which exhibits nonlinear behavior, more accurately and therefore provide better results (Adamowski et al., 2012).

Besides that, most classical parametric machine learning models, such as linear or polynomial regression, only generate a single output value as a prediction for every input value provided by a certain dataset, resulting in a single function that best fits the observed data points, while disregarding every other potential function which could also be used to depict a certain dataset, as illustrated on the left side in Figure 21. Other methods, such as Gaussian process regression (GPR), on the other hand do not only provide the expected function, but also offer a corresponding empirical confidence interval that varies in dependence with the certainty of the model, which can be seen on the right side of Figure 21 (Shi, 2019). This offers an advantage, when making decisions based on the foundation of the predictions, since the indicated certainty of the regression analysis makes one less susceptible to erroneous conclusions based on the mean value.

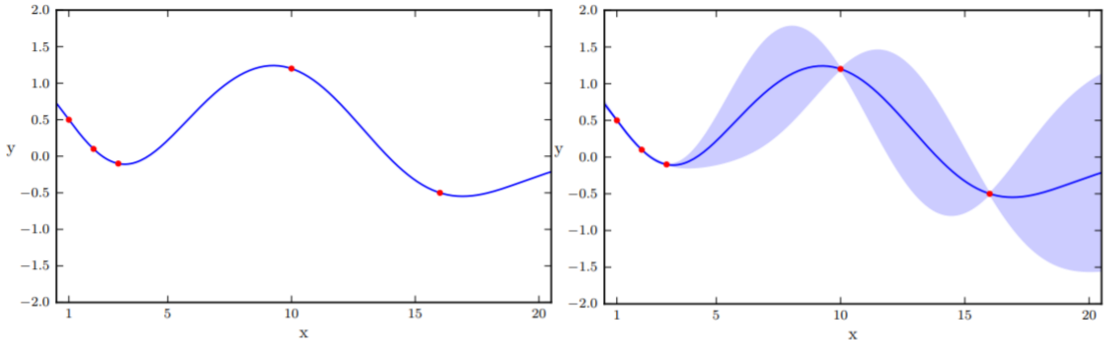


Figure 21 Comparison between a polynomial regression (left) and a Gaussian process regression (right), Source: Shi (2019)

Besides Gaussian process regression, there are also other regression based on machine learning methods, such as artificial neural networks, which can be applied for such applications.

The innovative approach of this master thesis is that, in contrast to previous studies that relied on climatic data provided by weather forecasts or weather predictions and were thus able to predict water demand over short or medium-term time periods, historical data has been combined with climate projections and thus enabling to provide long-term predictions (over the next several decades) of the future water demand.

The following chapters should act as a brief introduction into the basics of Gaussian process regression and are merely meant to provide the reader with the necessary knowledge in order to be able to understand the calculations carried out in the further course of this thesis. Therefore, it does not claim to represent a complete mathematical description or derivation of Gaussian processes or Gaussian process regression.

2.4.1 Introduction to Gaussian process regression

Gaussian process regression is a method used for interpolation, which is based upon Gaussian processes. Since they are predicated on the Gaussian distribution, both Gaussian processes and Gaussian process regression were named after the German mathematician and physicist Carl Friedrich Gauss. At first, Gaussian process regression was applied in the scientific field of geostatistics, where it is also known as Kriging and was utilized to interpolate geological data from unsampled or not sampleable locations. Since then, its scope of application has expanded and nowadays, it is used to provide predictions in various scientific branches, including the financial and pharmaceutical sectors, to name but two. There exist two approaches to developing Gaussian process regression models, namely the weight-space view and the function-space view. This work will focus on the visualization of Gaussian process regression by using the function-space view. According to the function-space view, Gaussian processes define the probability distribution over functions and consider inference directly taking place in the function space (Rasmussen et al., 2006).

Since Gaussian processes can be visualized as probability distributions over functions, Bayesian inference can be applied to update the probability distribution over the possible functions according to the knowledge gained from observed data points (Knagg, 2019). In the following section, the aim is to illustrate the operation of Gaussian process regression using Bayes' theorem and Bayesian inference.

2.4.2 Bayes' theorem and Bayesian inference

Bayes' Theorem is a mathematical equation, in which prior knowledge and beliefs can be incorporated to calculate conditional probabilities, also known as posterior probability distributions (Stanford Encyclopedia of Philosophy Archive, 2003).

The following formula displays the mathematical representation of the Bayes' theorem:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \tag{1.3}$$

with

$P(A)$: Prior (probability of observing the event A)

$P(B)$: Evidence (probability of observing the event B)

$P(A|B)$: Posterior (probability of event A occurring given that event B is true)

$P(B|A)$: Likelihood (probability of event B occurring given that event A is true).

Bayesian inference is the process of deducing properties from the probability distribution of a dataset using Bayes' theorem, which means that observed values are used to update our knowledge and beliefs about a certain model (Brooks-Bartlett, 2018).

In the context of Gaussian process regression, the prior probability distribution can be described as the distribution of the data, which is believed to occur based on preceding knowledge before any data has actually been observed. When conducting a regression analysis, this means that the functions that are incompatible with our prior can be disregarded, whereby the likelihood determines the definition of incompatibility in regard to the prior. The remaining functions are considered to be functions of the posterior. In the event that there is no prior knowledge or belief of the data, the mean can be considered as 0, as illustrated on the right side of Figure 22. This lack of knowledge results in a wide variety of sampled functions, since a pre-selecting of functions cannot take place, as can be seen on the left side of Figure 22.

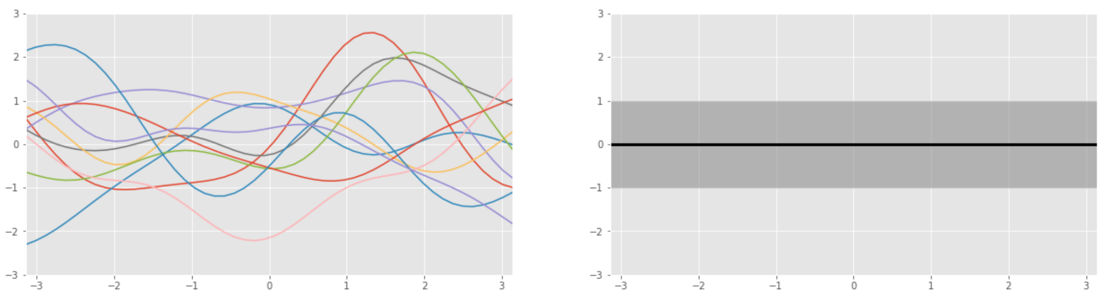


Figure 22 Resulting functions (left) and the mean function and standard deviation in the case that the mean function is equal to zero (right), Source: Knagg (2019)

Once new evidence is presented, as illustrated by four data points in Figure 23, the belief system can be updated by calculating the posterior probability distribution.

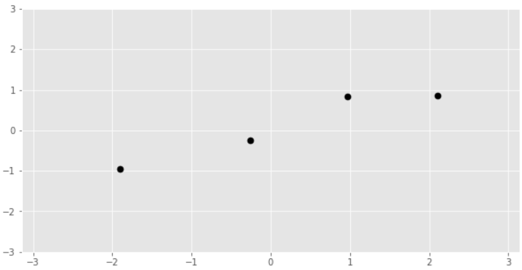


Figure 23 The introduction of evidence displayed as data points, Source: Knagg (2019)

This results in the selection of functions, which fit the observed data points more precisely, as depicted on the left side of Figure 24. Furthermore, it can be observed that the probability distribution of the functions has also changed according to our updated belief system or posterior and has been adjusted to cross through the data points. The expected function or mean, pictured as a black graph in Figure 24, is formed by calculating the mean value of the newly selected functions. The uncertainty of the model at and in the near vicinity of the observed data points is low and increases the further away one moves from the data points.

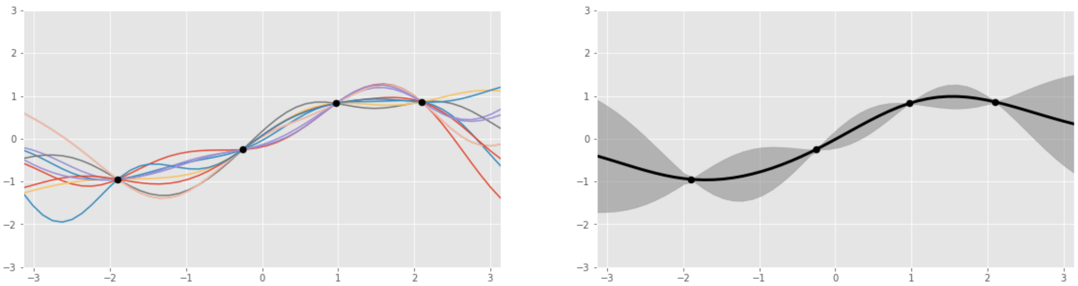


Figure 24 Resulting functions (left) and updated mean and standard deviation (right) after the introduction of evidence, Source: Knagg (2019)

This cycle can be repeated any number of times as new insights or data points become available, resulting in an increasing certainty of the model. The model can now also be used to compute the value of data points, which have not been observed yet, while also supplying the certainty of the computed predictions.

2.4.3 Gaussian process regression

After a short introduction into the operation of a Gaussian process regression, the procedure of the regression analysis as well as important parameters, their influence and importance for the process will be explained in the following chapters. These are based predominantly on the standard work for Gaussian process regression by Rasmussen, Williams (2006). A Gaussian process can be defined as a collection of random variables, any finite number of which are jointly Gaussian distributed. Gaussian processes are determined entirely by their mean function $m(x)$ and their covariance function $k(x)$, which is also known as the kernel. The mean and covariance function can be defined as

$$m(x) = E[f(x)], \tag{1.4}$$

$$k(x, x') = E[(f(x) - m(x))(f(x') - m(x')], \tag{1.5}$$

with x and $f(x)$ being the input and output values of the observed data points, which are also known as training data, and x' and $f(x')$ being the input and output values of the to be predicted data points, also known as test data. As such the prior of a Gaussian process can be written as

$$f(x) \sim GP(m(x), k(x, x')). \tag{1.6}$$

For a finite set of data points, the joint distribution $p(f(x_1), \ldots, f(x_n))$ of the output values $f(x)$ itself is Gaussian normal distributed $N()$ and can be described as

$$p(f|X) = N(f|\mu, K), \tag{1.7}$$

where $\mu = (m(x_1), \ldots, m(x_n))$ and $K_{ij} = k(x_i, x_j)$.

Knowledge or beliefs can be incorporated into the prior distribution through the selection of the mean and the covariance functions, which is called surrogate model selection (see Chapter 3.2.1.3). Most of the time the mean function is constant, being either zero or the mean of the training dataset. The covariance function on the other hand needs to be selected. Commonly used covariance functions include the constant kernel, the linear kernel, the squared exponential (SE) or radial basis function (RBF) kernel and the Matern kernel. In addition, covariance functions can also be summed up, through which new covariance functions can be generated.

In the further course of this chapter the radial basis function (RBF) covariance function, with mean function $m(x) = 0$, will be used as an example to illustrate how Gaussian process regression operates. Covariance functions are used to specify the covariance between pairs of random variables as follows:

$$cov(f(x), f(x')) = k(x, x') = \exp\left(-\frac{1}{2}|x - x'|^2\right). \tag{1.8}$$

In this case for the sake of simplicity we will consider that the observed data is noise free and that the characteristic length-scale l equals 1. Assuming a training dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$ with n observations and the function output f, where x represents an input vector and y represents a scalar output, the so-called design matrix X can be aggregated. In a similar way, the matrix of a test data X_* containing n_* observations can be aggregated.

If the function output of the test data f_* is to be determined, the prior distribution of the Gaussian process needs to be converted into a posterior distribution. Since the outputs of the training data f and the outputs of the test data f_* are joint Gaussian distributed they can be written as

$$\begin{bmatrix} f \\ f_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X, X) & K(X, X_*) \\ K(X_*, X) & K(X_*, X_*) \end{bmatrix}\right). \tag{1.9}$$

If there are n training observations and n_* test observations, the $n \times n_*$ matrix of covariances assessed at all pairs of training and test points is denoted as $K(X, X_*)$ and likewise for the other entries.

To obtain the posterior distribution over functions, we need to limit this joint prior distribution to include solely those functions that correspond to the observed training data. When applying the principles for the conditioning of Gaussians, the following equation is obtained for the posterior distribution

$$f_*|X_*, X, f \sim N(K(X_*, X)K(X, X)^{-1}f,\ K(X_*, X_*) - K(X_*, X)K\big(X, X\big)^{-1}K(X, X_*)\big). \tag{1.10}$$

Test data outputs f_* can now be sampled from the joint posterior distribution by evaluating the mean and covariance matrix from the equation above.

In more realistic settings, we typically only have access to noisy representations of functions, which can be expressed as $y = f(x) + \varepsilon$. This results in the following formulation of the covariance

$$cov(y, y') = k(x, x') + \sigma_n^2 \delta_{xx'}, \tag{1.11}$$

where $\delta_{xx'}$ is the Kronecker delta which is one if $x = x'$ and otherwise zero.

For the sake of simplicity, the determination of the posterior distribution of a model setting with noise will not be discussed. Rather, the following is limited to the effects of the adjustments that can be achieved by modifying the variable parameters of the covariance function.

In the context of Gaussian process regression, most of the covariance functions have free parameters. The radial basis function covariance function is denoted as follows

$$cov(f(x), f(x')) = k_y(x, x') = \sigma_f^2 \exp\left(-\frac{1}{2}|x - x'|^2\right) + \sigma_n^2 \delta_{xx'}, \tag{1.12}$$

with l>0 and σ_f^2>0 and where the covariance is denoted as k_y as it is for the noisy targets y rather than for the underlying function f. One can observe that the three parameters length-scale l, the signal variance σ_f^2 and the noise variance σ_n^2 can be varied. These variable parameters are called hyperparameters. Rasmussen, Williams (2006)

The influence of the hyperparameters on the selection of the functions is summarized in the following paragraph with the help of Figure 25.

Correlation length l: The correlation length is a measure of the constraint between height displacements of neighboring points and is significant when the points are within the correlation length and negligible when they are outside of it. Lower correlation length values result in a smaller influence of the neighboring point, as illustrated in the top left graph in Figure 25, and vice versa, as illustrated in the top right graph in Figure 25.

Signal variance σ_f^2: The signal variance is responsible for the amplitude of the functions. This can be observed by the fact that the uncertainty outside the training dataset is much higher in the middle right graph, than in the middle left graph of Figure 25.

Noise variance σ_n^2: The noise variance depicts the noise level in the training data. Larger noise values result in rougher estimations, which avoid overfitting to noisy data, as can be seen in the bottom two graphs in Figure 25 (Krasser, 2018).

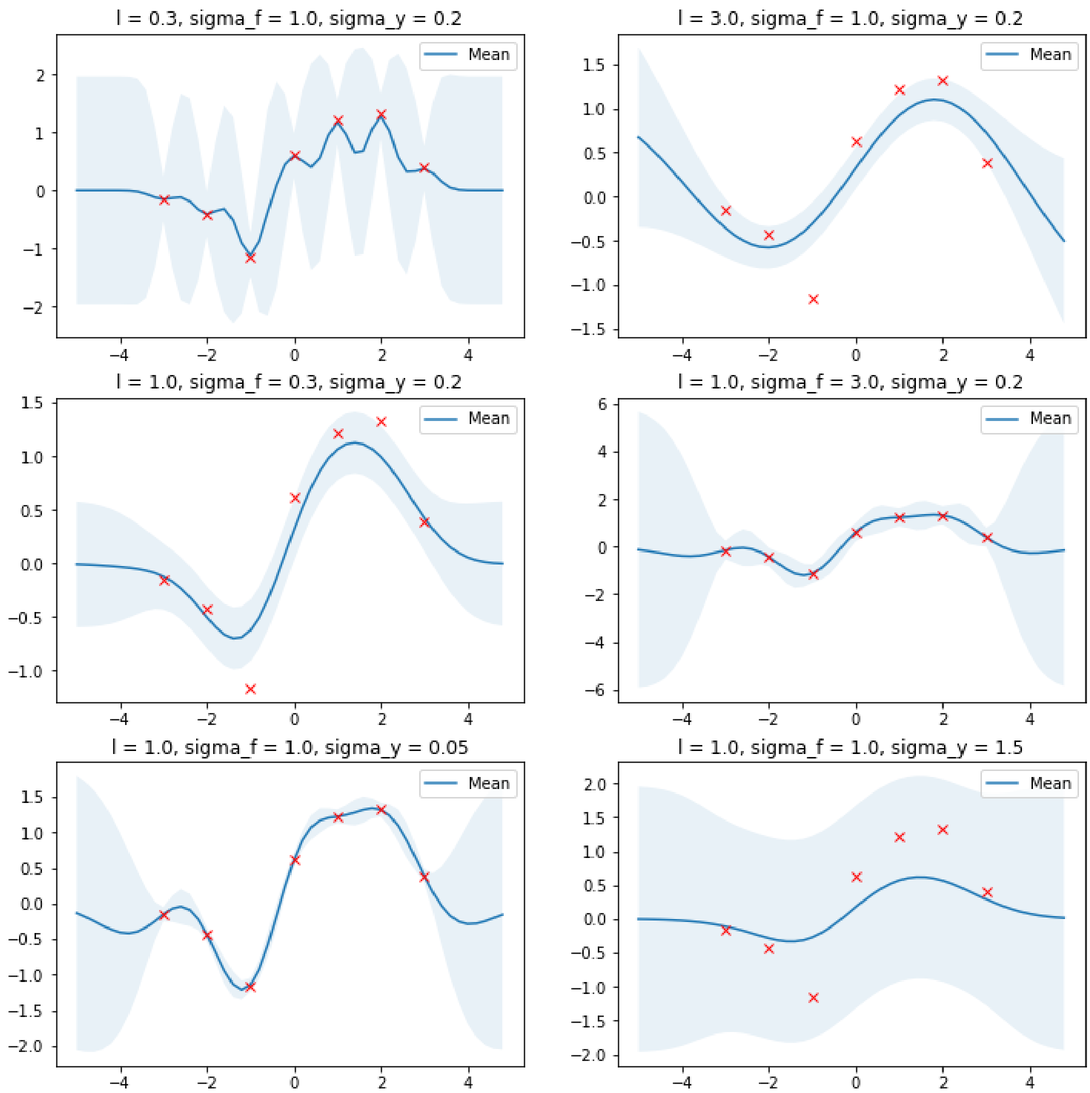


Figure 25 The influence of the hyperparameters on the selection of the functions and standard deviation, Source: Krasser (2018)

Surrogate model selection

Surrogate model selection refers to the selection of the mean and covariance functions as well as the setting up of the hyperparameters of the covariance functions. Since it is not always clear from the beginning which covariance function would fit the observed dataset most optimally, in such cases it is advisable to try several covariance functions or combinations of these. Furthermore, it is beneficial to review literature to find out what kind of kernels were used to develop models for similar or related research questions (Rasmussen et al., 2006).

Selection of mean functions

As stated earlier it is common to use $m(x) = 0$ as the mean function. (Murphy, 2012).

Selection of covariance functions

Radial basis function kernel

The radial basis function kernel (RBF), also known as the squared-exponential kernel, is a stationary kernel, which is parameterized by a length scale hyperparameter l>0 and the signal variance hyperparameter σ_f^2 >0 (see Chapter 2.4.3). Since this kernel is infinitely differentiable, GPs which use a radial basis function kernel as a covariance function have mean square derivatives of all orders and are thus exceedingly smooth (Scikit-learn Developers, 2022a).

Matern kernel

The Matern kernel is a class of kernels, which are a generalization of the radial basis function kernel and are parameterized by an additional parameter ν, which controls the smoothness of the resulting functions. The higher the ν-value, the smoother the approximated function is. When, the Matern kernel is equal to the radial basis function kernel, while when ν = 0.5, the Matern kernel is equal to the absolute exponential kernel. The parameter can also take the values ν = 1.5 or ν = 2.5, which results in once differentiable functions or twice differentiable functions, respectively.

The kernel is defined as:

$$k(x_i, x_j) = \frac{1}{\Gamma(\nu)2^{\nu-1}}(\frac{\sqrt{2\nu}}{l}d(x_i, x_j))^{\nu}K_{\nu}(\frac{\sqrt{2\nu}}{l}d(x_i, x_j)), \tag{1.13}$$

where $d()$ is the Euclidean distance, K_ν is a modified Bessel function and $\Gamma()$ is the gamma function (Scikit-learn Developers, 2022b).

Validation of the model

Model-validation is a method that can be used for model selection. The main idea of validation is to divide the training set into two disjoint sets, one for training and the other for validation of the model. This allows for a model to be set up and to be evaluated according to its performance, which is used as a proxy for the generalization error, a measure that describes how precisely a model is able to predict unobserved data. It is recommended to choose a split of 70/30 or 80/20, which means that 70-80% of the observed data is used to train the model, while 20-30% of the observed data is used to validate the model. It is important to note that a model is never verified with the data it was trained with, since this procedure would falsify the results of the calculation. There are two possible ways to select validation data. One is to just randomly select data points out of the dataset, while the other option is to select the last 20-30% of the data sorted according to the independent variable. This is especially useful when the independent variable is time, and you want to determine how well the model will predict future values. The validation of the model needs to be conducted for each dataset individually, since it can only provide how well the model works for a certain dataset (Rasmussen et al., 2006).

Coefficient of determination R^2

One validation method that can be used is the calculation of the coefficient of determination R^2, or also known as the Nash-Sutcliffe model efficiency coefficient

(NSE). The coefficient of determination R^2 is used as an indicator to describe the quality of the surrogate model, meaning how good a model fits a certain dataset. As a result, it can be used to evaluate how well unobserved samples will be predicted by the model. The best possible score a model can reach for the coefficient of determination is 1.0, which means that the model would predict the value of an unobserved data point exactly. When the coefficient of determination is 0 it means that the prediction capacity of the model is as good as the mean value, while a negative coefficient of determination means that the prediction capacity of the model is worse than the mean value. Models with a R^2-value of ≥0.55 are considered to supply sufficient predictions for the output values, whereas models with a R^2-value of <0.55 are considered to supply insufficient predictions for the output values. It can be concluded that, the closer the R^2-value is to 1, the stronger the correlation between the dependent and the independent variables.

If $\hat{y}_i$ is the predicted value to the corresponding true value y_i for a total of n samples, the coefficient of determination R^2 can be defined as:

$$\mathrm{R}^2(\mathrm{y}, \hat{\mathrm{y}}) = 1 - \frac{\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2}{\Sigma_{i=1}^{n}(y_i - \bar{y})^2}, \tag{1.14}$$

where $\bar{y} = \frac{1}{n}\Sigma_{i=1}^{n} y_i$ and $\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2 = \Sigma_{i=1}^{n}\epsilon_i^2$. Since the coefficient of determination is dataset dependent, it is not comparable across different datasets (Scikit-learn Developers, 2022c).

Over- and Underfitting

When setting up surrogate models, one wants to ensure, that it fits the available (validation) dataset as optimally as possible. In this process, care needs to be taken, that the surrogate model does not adapts too much to the training data points, which is called overfitting as illustrated in the right graph of Figure 26, or that it does not adapt enough to the training data, which is called underfitting as pictured in the left graph of Figure 26 (Murphy, 2012).

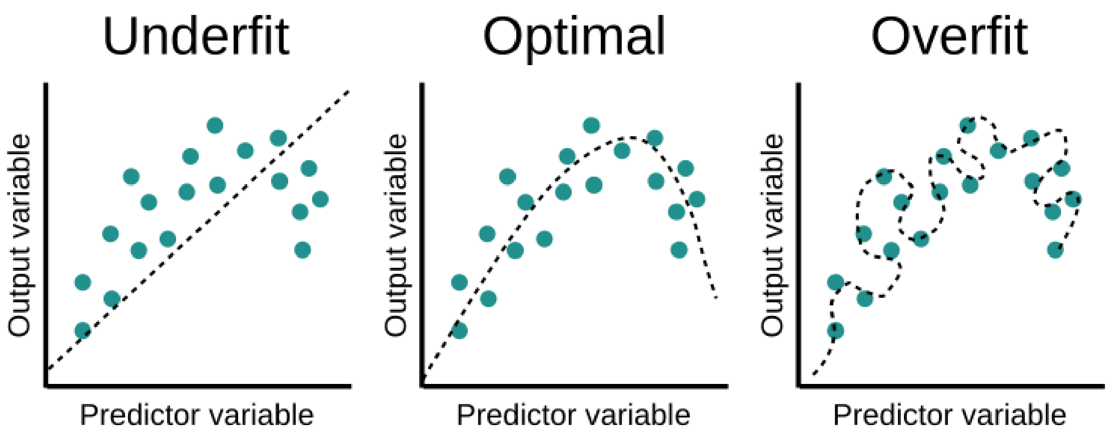


Figure 26 Graphical representation of a underfitted model (left), an optimal model (middle) and an overfitted model (right), Source: Rathod (2022):

To prevent over- or underfitting of the surrogate model, R^2-surrogate model assessment can be carried out (see Chapter 3.2.1.3). In this context the surrogate model would be considered to be underfitted, if the resulting R^2-value were low for the training as well as the test dataset, while the surrogate model would be considered to be overfitted, if the resulting R^2-value were high for the training dataset, but low for the validation dataset.

Advantages and Disadvantages of Gaussian process regression

Having introduced and outlined the principles of operation of Gaussian process regression in the preceding sections, the advantages and disadvantages of the GPR will be discussed briefly. A brief summary of the main advantages and disadvantages of Gaussian process regression are listed in Table 2.

Table 2 Summary of the advantages and disadvantages of Gaussian process regression (Knagg, 2019), (Rasmussen et al., 2006)

Advantages	Disadvantages
Unlike artificial neural networks, GPRs provide good results even with small datasets	Computational cost of predictions (cost increases cubically with the number of training samples)
Possibility to incorporate expert/prior knowledge and beliefs (surrogate model selection)	Polynomial chaos expansion needs assumptions about the parameter distribution
Offers predictions of the expected values and captures the model uncertainty	

Implementation of Gaussian process regression

There are several general-purpose programming languages (GPLs) that can be used for the implementation of Gaussian process regression, for instance C, C++, MATLAB, or Python. The syntax of Python is considered to be user-friendly, and it is regarded as an intuitive programming language, which makes it especially susceptible for inexperienced programmers. Furthermore, it facilitates many scientific and data-based libraries, in particular NumPy, Pandas, Matplotlib or Scikit-learn, which assist the programmer in the fields of machine learning, data science, data visualization and many more. In addition, it is an open-source programming language, which is one of the reasons why so many users and library developers decide to work with this particular programming language. Several libraries, such as scikit-learn, Gpytorch and GPy, can be used for the implementation of Gaussian process regression. (Kumar, 2018).

3 Methodology

This master thesis was carried out in cooperation with the Chalmers University of Technology, Department of Architecture and Civil Engineering, the University of Stuttgart, Institute for Modelling Hydraulic and Environmental Systems and the consultancy firm RBS wave GmbH as part of the internal research project "Influence of climate change on drinking water supply". Within the scope of this work, questions regarding the development and safeguarding of the quantitative aspects of the drinking water supply in relation to climatic developments are to be answered. The aim is to offer water utility companies the opportunity to get an overview of possible regional climatic developments and to demonstrate the resulting impact on their own drinking water supply. In addition, recommendations are drawn up with which the establishment of a safe and sustainable drinking water supply is possible.

The basis for this master's thesis is the first and second part of the research project in the form of a bachelor's thesis by Mr. Marcel Gerigk (B.Eng.) at the Esslingen University of Applied Sciences, Faculty of Building, Energy and Environmental Technology and a master's thesis by Ms. Selina Hüsam (M.Sc.) at the University of Stuttgart, Institute for Sanitary Engineering, Water Quality and Solid Waste Management. Furthermore, the processing of the task is based on the findings of previous literature research. In the first two parts of the research project, the study area was divided into five climatic zones on the basis of meteorological data and, with the help of questionnaires, supply data from water supply companies in the respective climatic regions were collected. In the course of the research project the questionnaire has been answered by a total of 60 water supply companies from the federal states of Baden-Württemberg, Bavaria, Rhineland-Palatinate, Saarland and Hesse. The data collection relates to the period 2010 - 2020. Furthermore, the water supply companies were also assigned location-related climatic data from the German Weather Service. With these datasets, an attempt was made to carry out initial projections for the development of the water consumption based on climatic parameters. However, these projections were set up by determining the dependency between an individual climatic parameter and the water consumption and by extrapolating it linearly, not taking actual projected climate data into account. The projections therefore only considered the dependency of a single climate parameter on water consumption and did not consider how combinations of parameters influence the water consumption.

As part of this master's thesis, a prognosis tool was therefore developed with which, on the one hand, it can be determined how reliably climatic parameters can be used to predict the water consumption of individual water utility companies and, on the other hand, can predict the future water consumption of a water utility company or within a climate zone. To achieve this, the datasets collected in the scope of the research project as well as climate data projections by the German Weather Service were used, on the basis of which the water supply companies were first analyzed individually, before developing forecast scenarios for each of the five climatic zones by comparing the results of the individually analyzed water supply companies. Based on the results of the analysis, potential measures and adaptation strategies to mitigate the risks to the quantitative aspects of the drinking water supply caused by climate change were developed and existing data deficits as well as monitoring needs were identified.

3.1 Description of the study area and data collection

3.1.1 Description of the study conducted

As part of the first part of the research project "Influence of climate change on drinking water supply" by the consultancy firm RBS wave GmbH, climatic and supply-related data from the study area was collected and evaluated. For this purpose, a total of 92 publicly owned water utility companies from the study area located in Southern Germany, which represents 2.2% of all publicly owned water utility companies in the study area, were requested to take part in the survey conducted, from which 60 answered the questionnaire, 15 withdrew their participation due to a lack of capacity and staff shortages and 17 are yet to answer the questionnaire. The 60 participating water utility companies represent 1.4% of all publicly owned water utility companies located in Southern Germany. However, the drinking water provided by the participating water supply companies, which adds up to 257.4 million m³, cover 11.6% of the total amount of drinking water provided in the study area. Figure 27 shows an overview map of the surveyed water supply companies, marked as participating (green), unassessed (yellow) or not participating (red). The evaluation of the survey was anonymous, which is why each company was assigned a number.

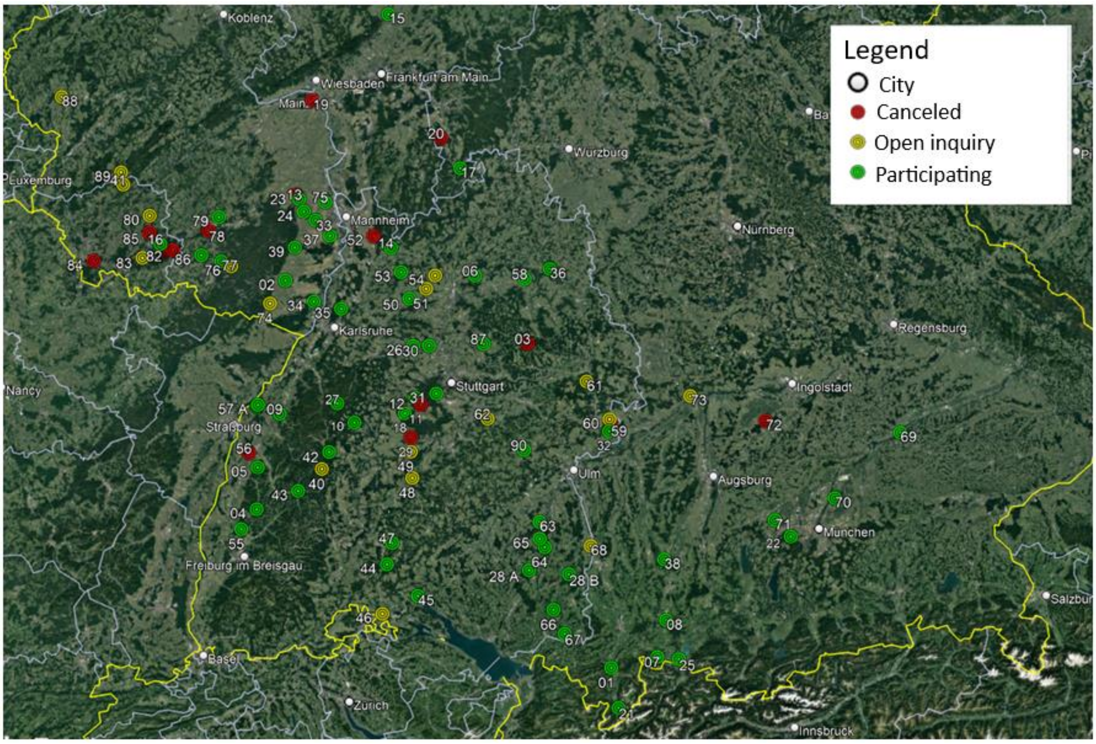


Figure 27 Overview map of the surveyed water utility companies in the study area Southern Germany

The questionnaire that was created for the research project aimed to collect the essential planning parameters and design variables of each water supply company. The data collected by the questionnaires included:

- The annual provision quantity,
- the monthly provision quantity of locally sourced water and long-distance water,

- daily peak values,
- population numbers,
- the net length,
- spring discharges and well yields including static groundwater levels and
- pipe burst statistics.

The influence of the population development on the water provision was circumvented, by only considering the per capita water provision, instead of the overall water provision.

The data was requested for the period from 2010 to 2020. When selecting the water supply companies for the survey, care was taken to include representative water utility companies of different sizes and supply structures. The distribution of the size classes and water supply structure can be found in Table 3 and Table 4.

Table 3 Classification of water supply companies according to size classes

Size class	Small	Medium	Large
Supply quantity [m^3/d]	< 1,000	1,000 – 10,000	≥ 10,000
CZ 1	0	4	0
CZ 2	2	4	0
CZ 3	6	4	2
CZ 4	6	14	6
CZ 5	0	8	4
Total	14	34	12

Table 4 Classification of water supply companies according to supply structure according to the code of practice DVGW 392

Supply class	1 (metropolitan)	2 (urban)	3 (rural)
Supply structure [$m^3/(km*a)$]	> 15,000	5,000 – 15,000	< 5,000
CZ 1	-	3	1
CZ 2	-	4	2
CZ 3	-	8	4
CZ 4	-	20	6
CZ 5	-	12	-
Total	-	47	13

In addition to the questionnaires that provided supply-related data, measured values from weather stations of the German Weather Service were evaluated in order to gain information about the prevailing climatic conditions. For this purpose, each water supply company was assigned a weather station, which is located in the shortest spatial distance from the supply areas of the water supplier. The data collected by the evaluation of the weather stations included:

- The maximum monthly temperature,
- the monthly average temperature,

- the monthly precipitation rate,
- the number of hot days per month,
- the number of summer days per month,
- the number of ice days per month and
- the monthly climatic water balance.

Depending on the prevailing local climatic conditions, the surveyed water utility companies were then assigned to climate zones. The basis for the formation of the five climate zones are the respective annual averages of the air temperature and the total precipitation rate for the years 1991 - 2021 from all climate stations of the German Weather Service. A value between 1 and 15 is assigned to these as shown in Table 5.

Table 5 Table for the determination of the values used for the classification into climate zones

Value	Temperature [°C]		Precipitation [mm/a]	
	Minimum	Maximum	Minimum	Maximum
1	-	< 5.0	> 1,800	-
2	5.0	5.5	1,700	1,800
3	5.5	6.0	1,600	1,700
4	6.0	6.5	1,500	1,600
5	6.5	7.0	1,400	1,500
6	7.0	7.5	1,300	1,400
7	7.5	8.0	1,200	1,300
8	8.0	8.5	1,100	1,200
9	8.5	9.0	1,000	1,100
10	9.0	9.5	900	1,000
11	9.5	10.0	800	900
12	10.0	10.5	700	800
13	10.5	11.0	600	700
14	11.0	11.5	500	600
15	11.5	12.0	400	< 500

Table 6 Table for the classification of weather stations into the climate zones

Sum	Climate zone
1 – 10	1
11 – 15	2
16 – 20	3
21 – 25	4
26 - 30	5

The sum of the values for the temperature and total precipitation then results in the classification into the climatic zones according to the sections, as listed in Table 6. Climate zone 1 covers a larger range of values than the other climate zones due to the fact that with a more specific subdivision the resulting climate zones would occupy a very small area. In the thus created zones, the number of water supply companies would be too small for a meaningful comparison with the other climatic zones. In this thesis, the water supply companies are assigned to the individual climatic zones and analyzed separately. The individual results are then used to create predictions for the individual climate zones. In the future, this will enable water supply companies to position themselves in accordance with their climate zone and to initiate possible measures to improve the water supply as well as the security of supply in their supply systems. The study area is henceforth divided, as shown in the following Figure 28.

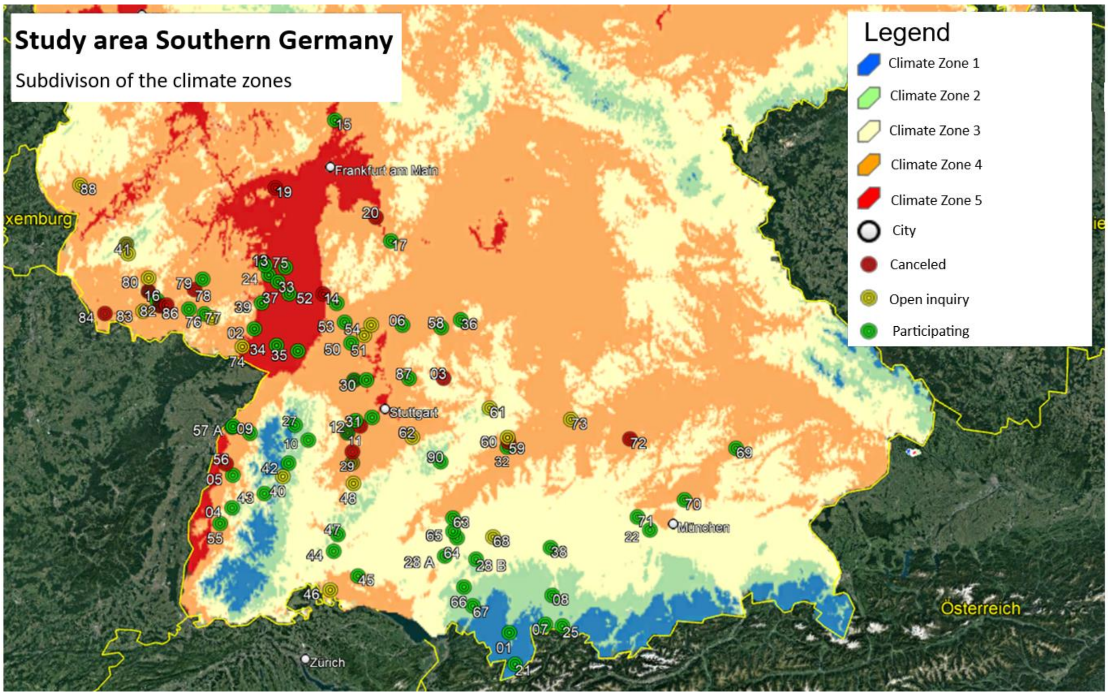


Figure 28 Subdivision of the study area Southern Germany into climate zones

In terms of surface area, the first climate zone covers 6.6%, the second climate zone 9.8%, the third climate zone 21.3%, the fourth climate zone 42.6% and the fifth climate zone 19.7% of the total surface area of the study area (see Table 7).

Table 7 Comparison between the specific area shares and the proportional number of water utilities in the five climate zones

Climate zone	CZ 1	CZ 2	CZ 3	CZ 4	CZ 5
Percentage of WUC [%]	6.6	9.8	21.3	42.6	19.7
Percentage of the study area [%]	5.0	7.2	23.7	48.8	15.3

The specific surface areas of the climatic regions in the study area roughly correspond to the relative proportions of the participating water supply companies in the analysis, which is why it can be assumed that the analysis of all water supply companies reflect the entire study area in a representative way. The participating water utility companies are assigned to climatic regions as follows: 4 water utility companies are located in the climate zone 1, 6 water utility companies are located in the climate zone 2, 12 water utility companies are located in each of climate zones 3 and 5, and 26 water utility companies in the climate zone 4. Figure 29 provides an overview of the distribution of the water utility companies.

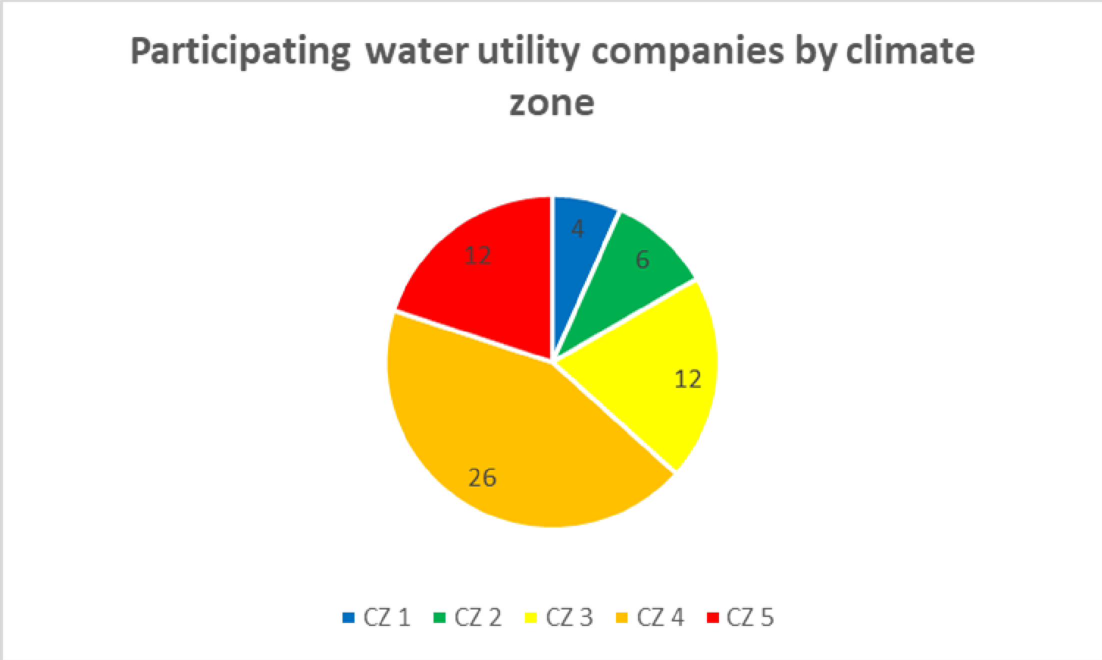


Figure 29 *Statistic of participating water utility companies by climate region*

Based on the analyzed weather stations, a rough comparison between the climate zones is made possible, which is used to classify the climatic zones in terms of temperature (see Figure 30) and precipitation (see Figure 31). The mean for South Germany results from the mean value of all weather stations used in the context of this work.

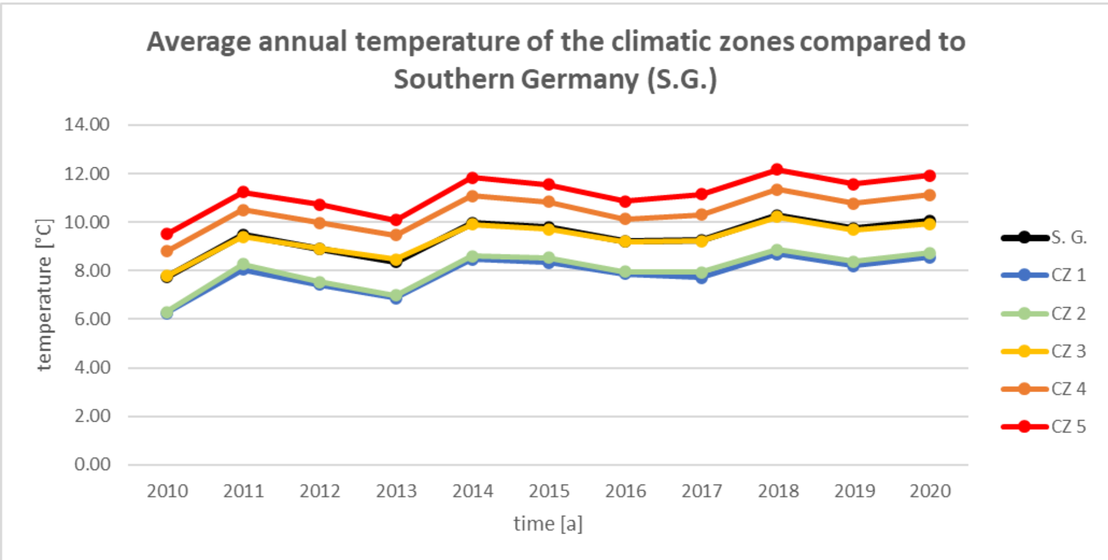


Figure 30 *Comparison of the average temperature of the climatic zones compared to the study area Southern Germany in the years 2011-2020*

In Figure 30 one can observe that the annual average temperatures of climate zone 3 is similar to the mean for the entire study area. The average annual temperature in climate zone 3 for the analyzed period 2011 - 2020 is 9.3 °C. At 11.3 °C, climate zone 5 is the warmest region and on average 3.3 °C warmer than climate zone 1. It can also be seen that climate regions 1 and 2 exhibit a similar climatic behavior. This is due to the fact that these statistics are based on the selective consideration of individual climate stations and not, as is the case for the formation of the climate zones, on the 30-year average of all climate stations of the German Weather Service in the study area. Due to the relatively small area and the associated small number of climate stations in both climate regions, the same climate stations were sometimes assigned to different water supply companies. In combination with the overall smaller amount of data, these climate stations carry more weight and result in a similar behavior of the climate zones 1 and 2. The following Figure 31 results from the graphic analysis of the annual amounts of precipitation in the individual climatic regions.

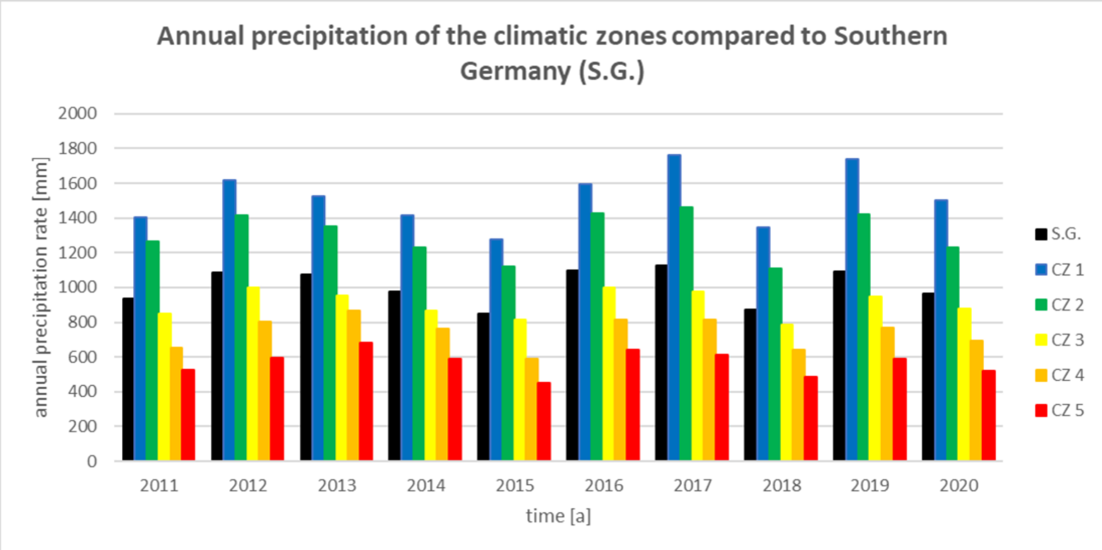


Figure 31 *Comparison of the annual precipitation rates of the climatic zones compared to the study area Southern Germany in the years 2011-2020*

It is evident that the highest precipitation rates occur in the climate zone 1 (1,519 mm/year) and 2 (1,303 mm/year). Climate region 5, on the other hand, on average only experiences 568 mm precipitation per year and is consequently the driest climate zone. All other absolute values regarding the annual average temperature and precipitation as well as the number of summer, hot and ice days are listed in Table 8.

Table 8 *Comparison of the climate zones and the study area based on the average annual values of selected climate parameters in the period 2011-2020*

Average annual values of selected climate parameters in the period 2011-2020							
Climate parameter	Unit	S.G.	CZ 1	CZ 2	CZ 3	CZ 4	CZ 5
Annual mean temperature	[°C]	9.3	8.0	8.2	9.5	10.6	11.3
Hot days	[-]	12	5	5	12	16	20
Summer days	[-]	48	33	31	50	60	68
Ice days	[-]	15	20	17	14	14	15
Annual precipitation rate	[mm/a]	1,008	1,519	1,303	908	740	568

Furthermore, the study area can be broadly divided into 6 different major hydrogeologic units, each of which was assigned a number as illustrated in Figure 32. On the basis of the hydrogeological units reduction factors for aquifers and spring discharges by 2050 were determined, as illustrated in Table 9. These are used in the later course of this thesis to estimate the decline in the available water supply.

Table 9 Classification of the hydrogeological units

Unit-Nr.	Hydrogeological Units	Reduction factor for aquifers	Reduction factor for spring discharges	color
1	Upper Rhine Rift, Mainz Basin and Nort Hessian Tertiary	0 – 5%	5 – 10%	
2	Alpine foothills	0 – 5%	5 – 10%	
3	West and South German stratigraphic and fracture clod country	5 – 10%	10 – 20%	
4	Alps	0 – 5%	5 – 10%	
5	West and Central German Basement	5 – 15%	15 – 30%	
6	Southwest German Basement	5 – 10%	10 – 20%	

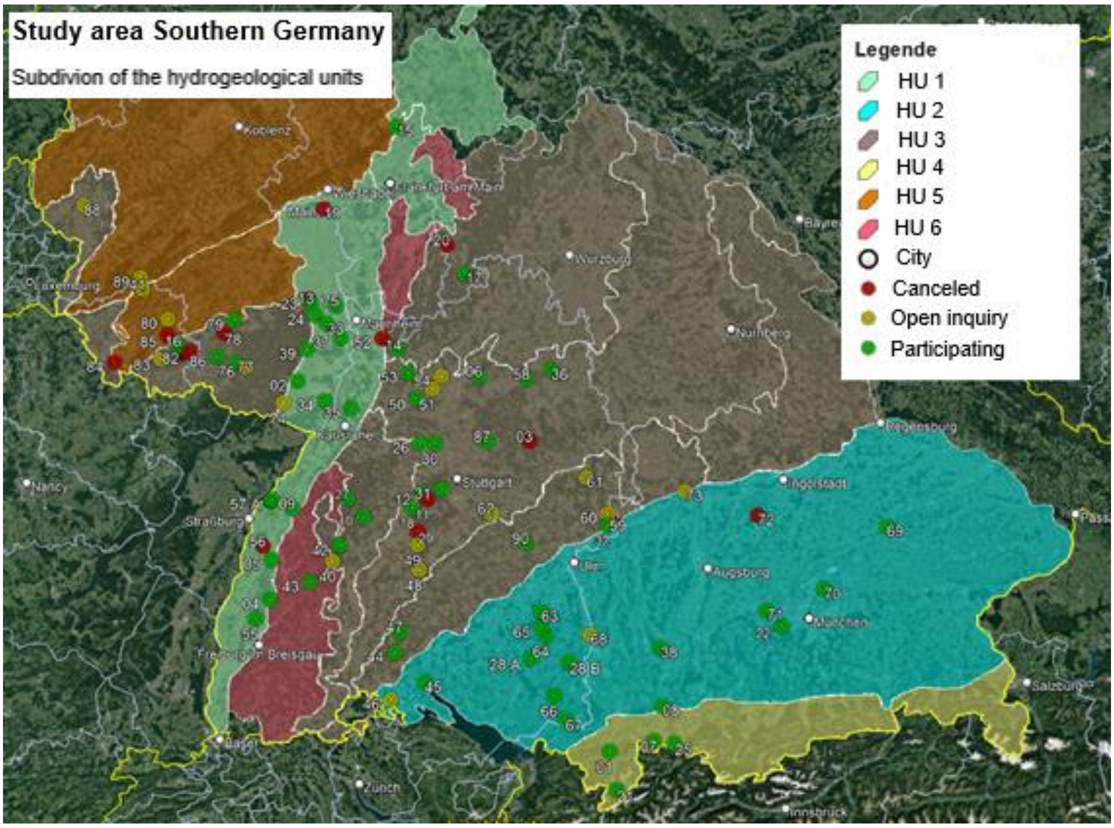


Figure 32 Overview map of the hydrogeological units in the study area of Southern Germany

3.1.2 Data collection

In order to create predictions in regard to the future water demand, within the framework of this thesis, data from the German Climate Atlas (German: Deutscher Klimaatlas) of the German Weather Service was requested. The German Climate Atlas is based on different climate scenarios of anthropogenic influence on the greenhouse gas emissions, as described in Chapter 2.2.3, and provides regional climate projections for the individual federal states and regions of Germany. Each of the three provided climate scenarios, in particular the scenarios RCP2.6, RCP4.5 and RCP8.5, is made up of different global and regional climate models that serve as the basis for its calculation. Thus, the German Climate Atlas displays a possible range of developments for a single climate scenario, rather than giving a single value, as can be seen in Figure 33 (Deutscher Wetterdienst, 2022o).

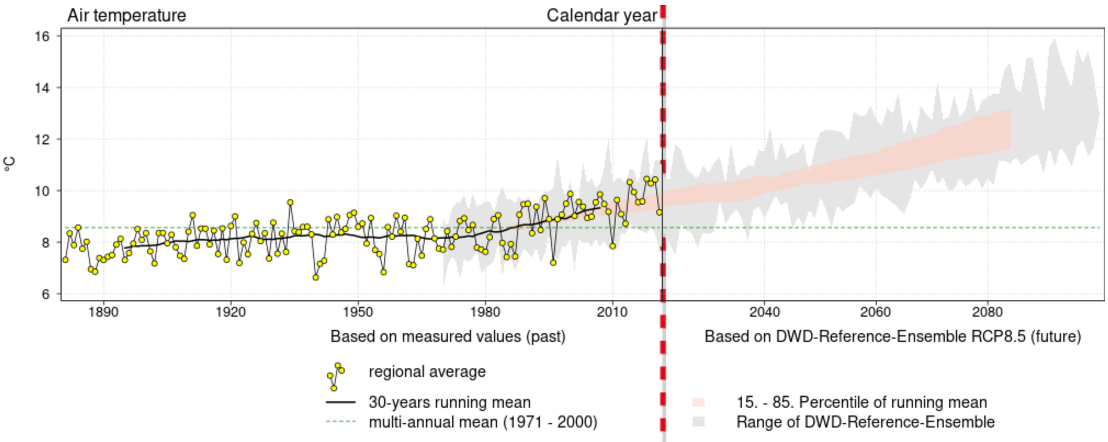


Figure 33 Graphical representation of measured values and projected ranges for the climate scenario RCP8.5 of the annual temperature in Germany, Source: Deutscher Wetterdienst (2022p)

The Figure shows the measured (yellow points) and projected values (gray and red areas) of the climate scenario RCP8.5 for the air temperature in Germany from 1880 to 2100. The gray area represents the range of all climate models of the single climate scenario, while the red area represents the 15th to 85th percentile of the running mean of all climate models. As climate projections do not precisely predict the climate, but rather point out general climatic trends, as described in Chapter 2.2.3, the measured and projected climate data are often given or presented as 30-year running means, to compensate for extreme fluctuations in the projections, as represented by the black curve and the red area in Figure 33. Since the goal of the analysis was to cover the whole range of possible climatic developments and the datasets from the German Climate Atlas are not freely available, it was decided to request the datasets for the two climate scenarios RCP2.6 and RCP8.5 from the German Weather Service. In this context, climate scenario RCP2.6 represents the "best-case" scenario, whereas climate scenario RCP8.5 represents the "Business-as-usual" or "worst-case" scenario. The climate scenario RCP2.6 was made up of 11, while the climate scenario RCP8.5 was made up of 20 individual climate models. Each climate model included quarterly or yearly predictions of the following climatic parameters:

- The average temperature,

- the precipitation rate,
- the number of hot days,
- the number of summer days and
- the number of ice days.

Since the climate scenarios and climate models of the German Weather Service refer to federal states and the region of Southern Germany, respectively, and no finer distinctions according to the climate zones is available, the projected climate data for Southern Germany was provided. This data was then adapted to the local climate conditions of the water supply companies. For this purpose, the difference between predicted and measured climate data for the period from 2011-2020 was formed and added or subtracted to the period from 2021-2090, as can be seen exemplarily in Figure 34. In this case, the average annual deviation of the measured temperature values between the water utility company 02 and Southern Germany was calculated, which in this case was 2.3 °C, and in a next step it was added to the predicted annual temperature values for Southern Germany, resulting in the projected temperature values for the water utility company 02.

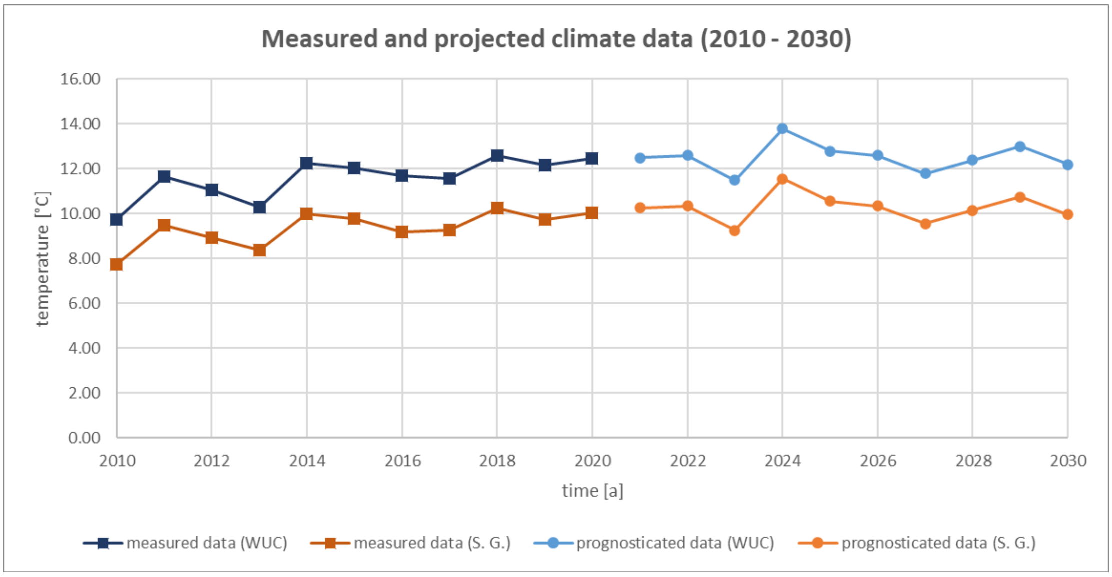


Figure 34 Comparison of the measured and projected climate data for the entire study area of Southern Germany and for the water utility company 02 in the period from 2010-2030

Due to time restrictions, this method was applied for three climate models of each climate scenario, resulting in six climate models overall. In each case, the most pessimistic, most optimistic, and a neutral climate model were selected, as illustrated in Figure 35.

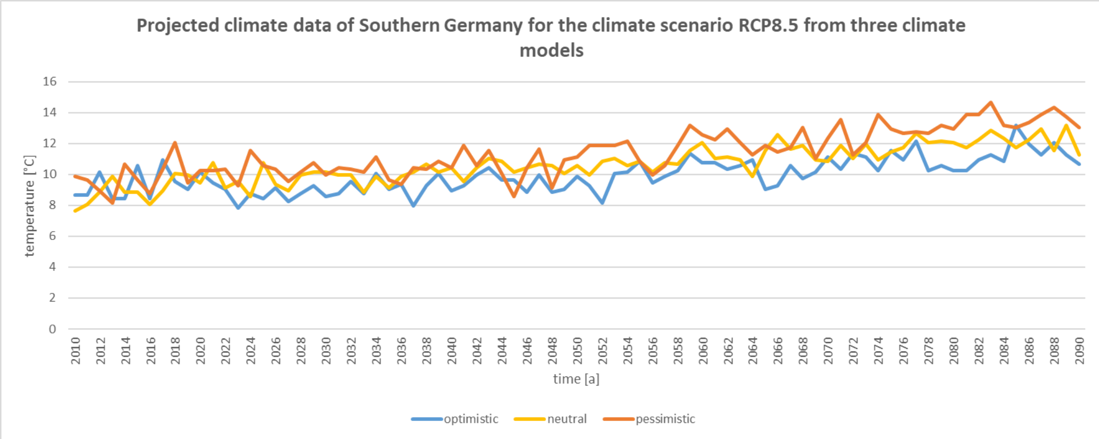


Figure 35 *Comparison of the temperature curves of three different climate models for the climate scenario RCP8.5 in the period 2010-2090*

Figure 36 and Table 10, shows an example of the development of a single climate parameter, the decadal average temperature, in this case for the water utility company 02, which is located in climate zone 5.

Table 10 *Development of the decadal average temperature for the water utility company 02 in the period 2011-2090*

Decadal average temperature [°C]						
time period	RCP2.6			RCP8.5		
	(1)	(2)	(3)	(1)	(2)	(3)
2011-2020	11.73	11.73	11.73	11.73	11.73	11.73
2021-2030	11.55	12.09	11.64	12.65	12.37	11.99
2031-2040	11.62	12.48	12.14	13.03	12.54	11.88
2041-2050	11.58	12.62	12.29	13.31	13.11	12.16
2051-2060	11.48	12.54	12.28	14.31	13.44	12.63
2061-2070	11.39	12.68	12.39	14.70	13.92	12.93
2071-2080	11.22	12.43	12.12	15.48	14.43	13.56
2081-2090	11.10	12.32	11.92	16.37	14.89	13.99

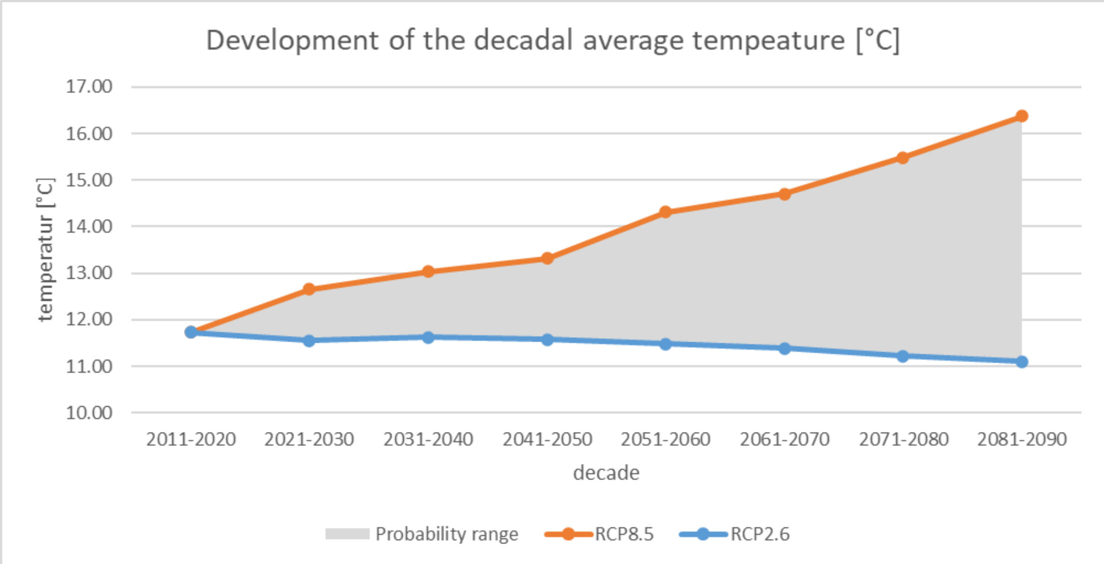


Figure 36 *Graphical representation of the development of the decadal average temperature for the water utility company 02 in the period 2011-2090*

It can be seen that the average temperature in the scenario RCP2.6 at best is expected to be decrease 0.8% per decade until the end of the study period, while the average temperature in the scenario RCP8.5 at worst is expected to increase 5.7% per decade over the same period. The projections of the other climate parameters for the water utility company 02 can be found in Appendix B.

3.2 Implementation of Gaussian process regression for the prediction of the future water demand in dependence of climatic parameters

The first two parts of the research project identified the relationships between the water consumption and individual climatic parameters, which were then used as the basis of initial water demand projections. These projections however only referred to a single climatic parameter at a time and did not consider the interaction between different climatic parameters, such as the temperature and the precipitation. In addition, these projections were made by using linear regression, which is not well suited since the projections exhibited a low coefficient of determination and were therefore subject to great uncertainties. Furthermore, the linear predictions only provide a point forecast, but no confidence interval with which the certainty of the calculation can be determined. For this reason, it was decided to use machine learning to incorporate the interaction of the various climatic parameters into a surrogate model in order to represent their influence on the water consumption as realistically as possible and, in a next step, to use the surrogate model to determine the future water demand based on projected climate data. Due to the limited amount of data available (each dataset consisting of roughly 130 values) it was decided to implement Gaussian process regression rather than artificial neural networks, since the former can achieve reliable results with small datasets, while the later requires large datasets to provide reliable results. For this implementation of the Gaussian process regression scikit-learn's Gaussian process package was chosen.

3.2.1 Dependence of the drinking water consumption in relation to climatic parameters

Amongst the 60 participating water utility companies 42 provided complete and usable datasets, as described in Chapter 3.1.1. From the remaining 18 datasets, 11 have shown to have gaps, some of which extend over several years, or only provided yearly values, but not monthly values, while the remaining 7 were submitted in later stages of the analysis and therefore could not be considered anymore. Since each complete dataset consists of a small number of about 132 data points, and the calculations and validation with an even smaller number of points would not provide a satisfactory result, it was decided to disregard the 11 incomplete datasets for the further analysis. The following eight input parameters were available for the analysis:

- The maximum monthly temperature (x1),
- the monthly average temperature (x2),
- the monthly precipitation rate (x3),
- the number of hot days per month (x4),
- the number of summer days per month (x5),
- the number of ice days per month (x6),
- the monthly climatic water balance (x7) and
- the number of the month (x8).

The first seven input parameters (x1-x7) are climatic factors and were provided by the German Weather Service, whereas the input parameter x8 is a temporal factor and was added as an additional parameter.

Figure 37 shows a section of the dataset of the water utility company 02.

date	month [-]	water provided [m³/month]	population number [-]	per capita water consumption [l/(C*d)]	monthly average temperature [°C]	maximum monthly temperature [°C]	number of hot days [-]	number of summer days [-]	number of icy days [-]	monthly precipitation rate [mm/month]	climatic water balance [mm/month]
January-10	1	242,085	43,469	180	-1	7	0	0	16	47	45
February-10	2	209,163	43,478	172	2	16	0	0	6	72	58
March-10	3	228,488	43,486	169	6	20	0	0	1	33	-7
April-10	4	259,181	43,495	199	12	26	0	1	0	35	-50
May-10	5	235,295	43,503	174	12	27	0	2	0	99	33
June-10	6	266,851	43,512	204	19	29	0	13	0	72	-43
July-10	7	304,761	43,521	226	21	35	11	18	0	72	-45
August-10	8	270,796	43,529	201	18	30	0	8	0	115	36
September-10	9	231,054	43,538	177	14	24	0	0	0	48	1
October-10	10	254,480	43,546	189	10	22	0	0	0	25	0
November-10	11	209,340	43,555	160	6	19	0	0	2	91	75
December-10	12	253,679	43,563	188	-1	6	0	0	15	144	141

Figure 37 Section of the dataset of the water utility company 02

3.2.1.1 Data scaling

Since the values of the individual climate parameters differ greatly and it should be prevented that one climate parameter influences the analysis greater than another one, the input parameters were scaled. For this purpose, an estimator, which scales and translates each feature individually such that it lies in between a given range, in this case between zero and one, was used. Scikit-learn Developers (2022d)

3.2.1.2 Data splitting

After that, in order to be able to validate the model, the training data was divided into a training set and a validation set. For this purpose, the respective datasets were divided in dependence of the time, since the aim of the calculations is to determine the future water demand and thus through this approach, which is also known as time-series forecasting, one can determine how well future data can be predicted. The data points before July 2017, which correspond to 77% of the entirety of data points, were used to train the model and the remaining data points from July 2017 to December 2020, which correspond to 23% of all data points, were used to validate the model. Figure 38 shows the division of the datasets into the training set (gray points) and a validation part (red points), as well as the calculated expected function (red graph) and the corresponding confidence interval (gray area), for the water utility company 24.

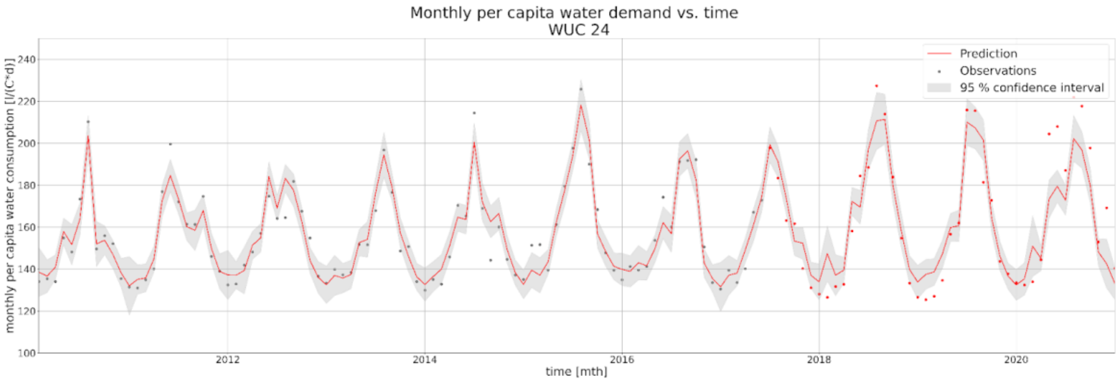


Figure 38 Graphical representation of the monthly water consumption in the period 2010-2020 of the Gaussian process regression of the water utility 24

3.2.1.3 Surrogate model selection

In order to analyze the water demand in dependence of climatic parameters, the most suitable surrogate model needs to be selected. Initially, therefore, an attempt was made to combine the datasets of the individual water suppliers from one climate zone to then use them to set up a single surrogate model for each climate region. However, this approach has proven not to be possible, since the supply structure and the consumption figures of each supply network and each supply area, even within a climate zone, are spread out too widely. Consequently, every dataset was analyzed individually, in order to figure out which input parameter combination and kernel provide optimal results. In this context, the Matern kernel was used as a covariance function, which had the advantage that four individual kernels can be obtained by simply changing the parameter, as described in Chapter 2.4.3. The results of the individual calculations for each dataset are presented in Appendix A. With a total of 42 datasets used for the analysis, each of which contains a set of eight input parameters, this resulted in a total of 255 input parameter combinations for each dataset. Taking into account that each input parameter combination needs to be calculated for each of the four Matern kernels, this results in 1020 calculations per dataset.

3.2.1.4 Validation of the surrogate model

In order to validate the surrogate model, the coefficient of determination R^2, also known as the Nash-Sutcliffe model efficiency coefficient (NSE), of each dataset needs to be determined individually. In particular, the coefficient of determination of a dataset is significant for the validation since it provides an indication of the accuracy of the prediction of unseen datapoints. In the further course, the coefficient of determination of the validation set serves as the main criteria for the decisions regarding the setup of the surrogate model.

3.2.1.5 Analysis of the input parameters and input parameter combinations

The analysis of the input parameters and their combinations is aimed to determine how well these are able to predict the water consumption. To evaluate the prediction performance of the surrogate model, which is trained on the training dataset, the coefficient of determination of the validation set is determined, which then can be used to conclude if individual input parameters exert influence on the water consumption, and if to what extent, or not. For this purpose, in a first step the individual input parameters were first compared with one another before the various input parameter combinations were compared with one another in the next step. In order to compare the individual input parameters, the coefficient of determination for each of the eight input parameters, using the 42 complete and usable datasets, was calculated. In this process, three variants were evaluated. The first one being the evaluation of all datasets, the second one being the evaluation of the datasets where a positive coefficient of determination was achieved and the third one being the evaluation of the datasets where a coefficient of determination of at least 0.55 was achieved. Since it occurred in some cases, that individual input parameters have produced the same results, multiple responses per dataset were possible. The results of the first analysis are illustrated in the figure below.

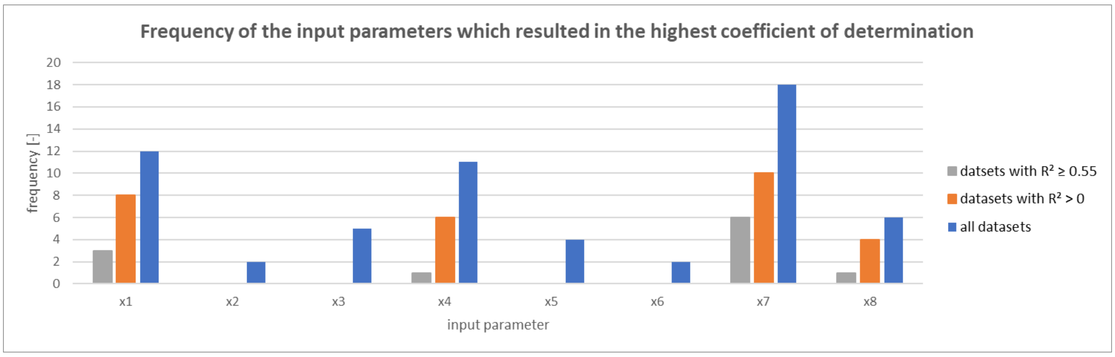


Figure 39 Frequency of the input parameters which resulted in the highest coefficient of determination

Figure 39 shows that the input parameters x7, x1 and x4 most often result in the highest values for the coefficient of determination in all of the three evaluated variants.

In the next step, the input parameter combinations that result in the highest values for the coefficient of determination were identified. However, since there are 255 possible input parameter combinations for each dataset and they could not be compared to one another due to time limitations, the individual input parameters that occurred in the input parameter combination with the highest coefficient of determination were determined. In this process, again three variants were evaluated. The first one being the evaluation of all datasets, the second one being the evaluation of the datasets where a positive coefficient of determination was achieved and the third one being the evaluation of the datasets where a coefficient of determination of at least 0.55 was achieved. The following figure shows how often individual parameters occurred within the input parameter combination that resulted in the highest coefficient of determination.

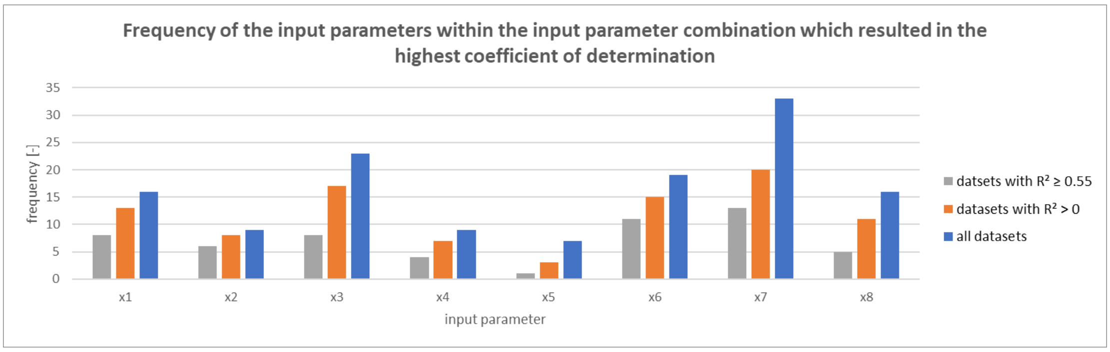


Figure 40 Frequency of the input parameters within the input parameter combination which resulted in the highest coefficient of determination

Figure 40 shows that the input parameters x7, x3 and x6 in particular occur most often in the input parameter combination, which results in the highest values for the coefficient of determination.

The following figure displays the obtained coefficients of determination for all 255 input parameter combinations of a single dataset, which are depicted as columns. The number of input parameters within the combinations increases from left to right, starting with single input parameters on the left and ending with the combination containing all eight input parameters on the far-right side. It can be observed that although in some isolated cases certain input parameter combinations produce higher results for the coefficient of determination, in general it can be said that the coefficient of determination increases with an increased number of input parameters within a combination. Furthermore, it can be observed that there are no outliers and also no large fluctuations between the last few input parameter combinations, which include 7 to 8 input parameters and are depicted as the columns on the far-right side of the graph. These combinations all achieve values of over 0.8 for the coefficient of determination.

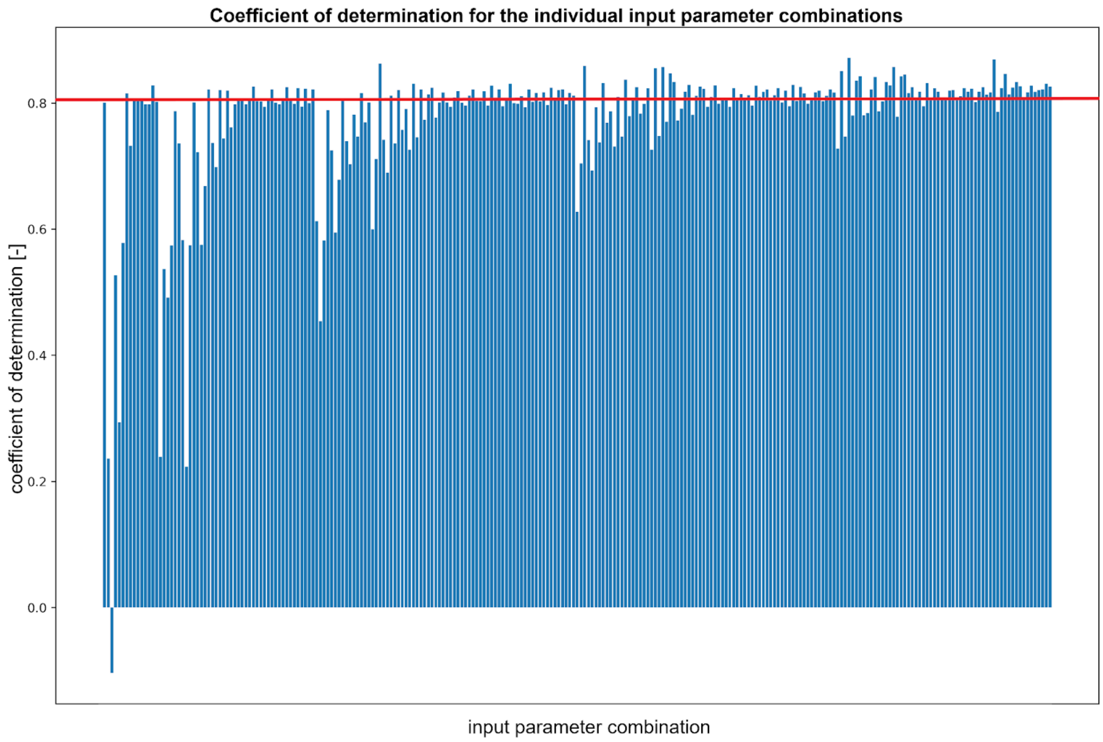


Figure 41 Coefficient of determination for all 255 input parameter combinations of the dataset of the water utility company 24

This behavior could be observed for the other datasets as well. As a consequence and since no single input parameter combination which led to the highest coefficient of determination across all evaluated datasets could be identified, all input parameters were considered for the subsequent calculations in order to minimize computation time.

3.2.1.6 Sensitivity analysis of the input parameters

After the input parameters and input parameter combinations have been evaluated, a sensitivity analysis of the input parameters was carried out, the aim of which is to determine which influence a single parameter has on prediction capacity of the surrogate model and hence the influence on the R^2-value. In this respect, the higher the resulting index of an individual parameter, the higher its influence is on the prediction capacity. Furthermore, an input parameter with a positive index means that it influences the prediction capacity of the surrogate model positively, while an input parameter with a negative index means that it influences the prediction capacity of the surrogate model negatively. For this purpose, the total sensitivity indices of each input parameter were determined. Figure 42, depicts the results of the sensitivity analysis for the datasets of the water utility companies 33 and 34, which are located in the same climate zone.

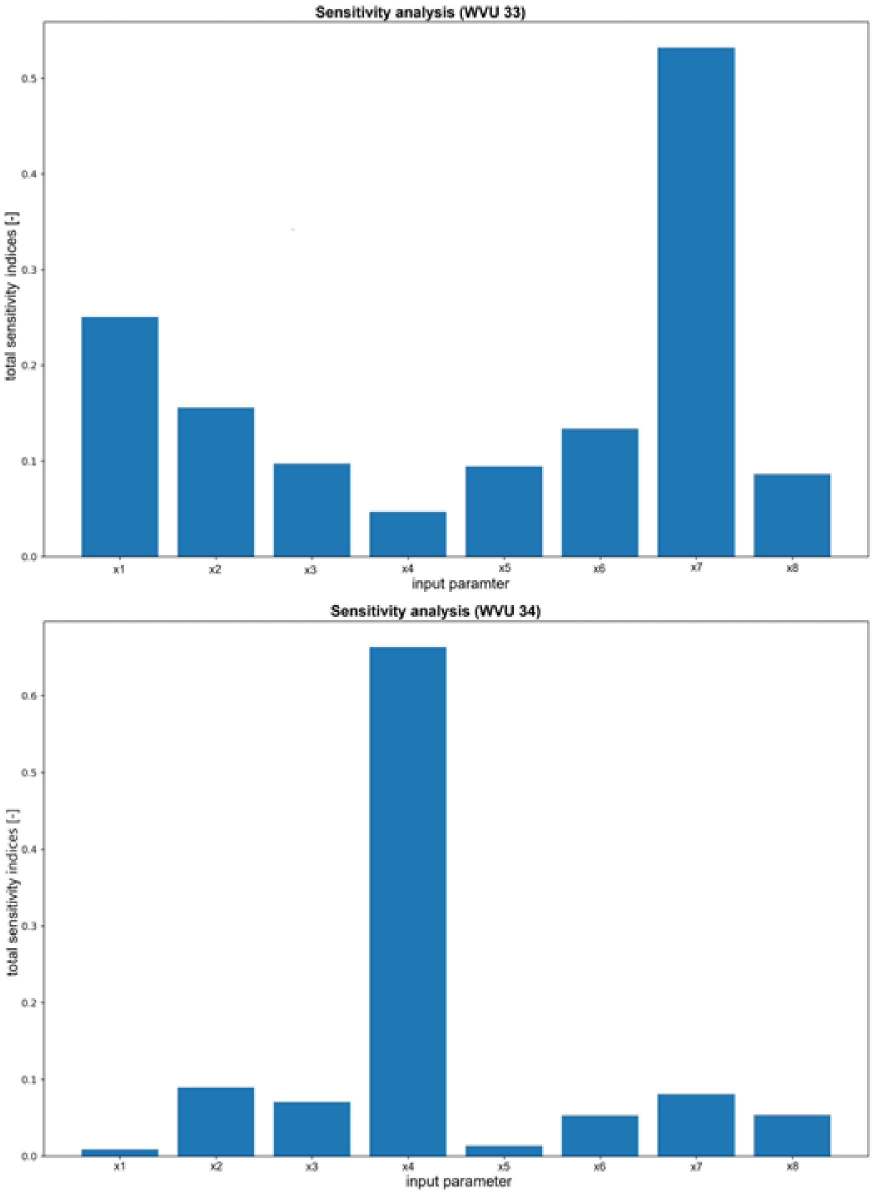


Figure 42 Sensitivity analysis of the individual input parameters for the datasets of the water utility companies 33 and 34

In Figure 42, it can be clearly seen that the extent for the total sensitivity indices of the individual input parameters vary widely between the two datasets and thus influence the model differently, although they are located in the same climatic zone. As a result, no single input parameter could be identified that, across all datasets, affects the model the most or at a constant rate. Furthermore, the extent of the individual input parameters changes every time input parameters are added or taken away. Thus, if one wants to generate insights into the influence individual input parameters exert on the model, it is advisable to consider this for each dataset independently. In addition, in scope of the performed sensitivity analysis, no input parameter was found that took on a negative value and would therefore negatively affect the prediction capacity of the model. Consequently, the further calculations were conducted with all available input parameters.

3.2.1.7 Analysis of the covariance function

The analysis of the covariance function is aimed to determine how the kernel choice affects the accuracy of the surrogate model and hence the projection of the water consumption. For this purpose, the coefficient of determination needs to be determined. In this analysis, the Matern kernel was selected, which results in 4 different kernels depending on the ν-value, as described in Chapter 2.4.3. In order to compare the performance of the different kernels the coefficient of determination for each of the eight input parameters, using the 42 complete and usable datasets, was calculated. In this process, three variants were evaluated. The first one being the evaluation of all datasets, the second one being the evaluation of the datasets where a positive coefficient of determination was achieved and the third one being the evaluation of the datasets where a coefficient of determination of at least 0.55 was achieved. Since it has occurred in some cases, that individual kernels have produced the same results, multiple responses per dataset were possible. The results of the covariance function analysis are illustrated in the figure below.

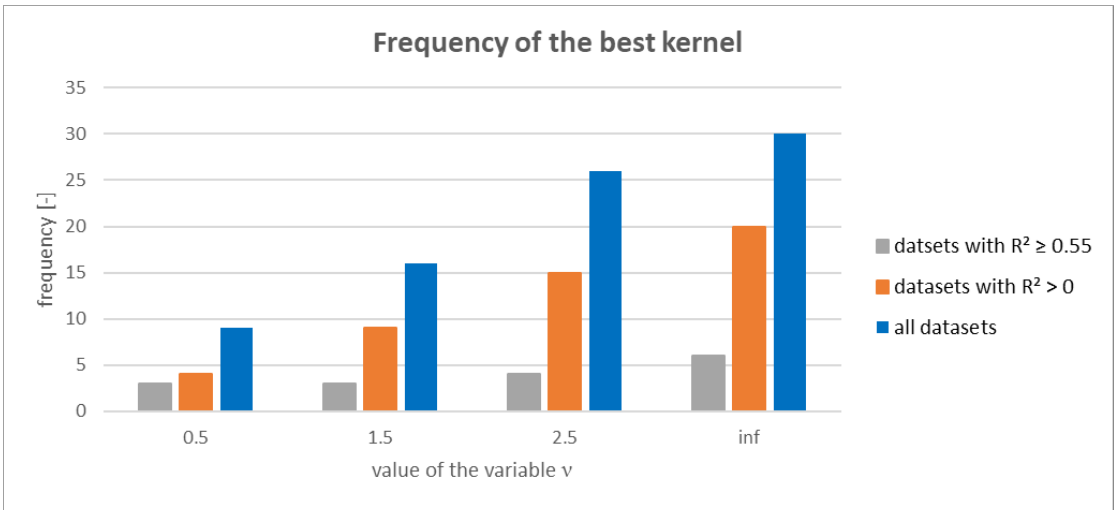


Figure 43 Frequency of the kernel which resulted in the highest coefficient of determination

Figure 43 shows that the radial basis function kernel most often results in the highest values for the coefficient of determination in all the three evaluated variants. Consequently, in order to minimize the computing time, the future calculations were all carried out with the radial basis function kernel as the covariance function.

3.2.1.8 Confounding factors

When performing the calculations, it was observed that for some datasets no satisfactory results could be determined, i.e., the coefficient of determination assumed low or negative values, which means that the prediction capacity of the model is worse than the mean value, as described in Chapter 2.4.3. Conversely, this implies that an increase in the climate parameters does not influence the drinking water demand. For this reason, a plausibility analysis was performed on the datasets that had low or negative coefficients of determination ($R^2 < 0.55$). In doing so, the datasets were checked for confounding factors that are not climate dependent and therefore might cause inferior results.

The following confounding factors were identified in the process:

- High water losses,
- a high share of large-scale consumers (e.g., industry),
- pronounced winter tourism and
- measurement inaccuracies or changes in the supply structure.

The individual confounding factors are briefly described in the section below.

High water losses

High water losses are an interfering factor for the analysis of the water consumption in connection to climate parameters. Water losses are a major problem in some cities and towns, where they are responsible for a large proportion of the overall amount of drinking water provided. These can be in the mid-double-digit range, with some water utilities companies in the study area having been found to have water losses of up to 50%. Since the water losses in the supply system do not occur constantly or in regular intervals, but oscillate and therefore falsify the actual water consumption, they represent a major challenge for the accuracy of the surrogate model. As a result, no clear relationship between the climatic parameters and water consumption could be established and therefore no satisfactory results for datasets with high water losses could be provided.

High proportion of large-scale consumers

An additional interfering factor for the analysis of the water consumption in connection to climate parameters is the high proportion of large-scale consumers. The influence of large-scale consumers is most noticeable in smaller cities and towns that are highly industrialized, where some large consumers within the study area have been found to purchase up to 30-60% of the total amount of drinking water provided. An example of this is the city of Sindelfingen, where one company alone purchases 60,000-90,000 m³ of drinking water per month, which accounts for 13-30% of the total drinking water provided by the local utility company. Since the water consumption of large-scale consumers often is not constant but oscillates strongly, e.g., depending on how much water is used to produce goods or cooling, it represents a major challenge for the accuracy of the surrogate model. Production facilities are also known to expand, which can lead to a sudden increase in the water consumption, as described in the sub-chapter 'Measurement inaccuracies or changes in the supply system' below and therefore lead to inaccurate results. As a result, no clear relationship between the climatic parameters and water consumption could be established and therefore no satisfactory results for datasets with a high proportion of large-scale consumers could be provided.

Pronounced winter tourism

Another interfering factor for the analysis of the water consumption in connection to climate parameters is pronounced winter tourism, which in this study area mainly affects water utility companies in climate zone 1 and partly in climate zone 2. In the areas of Southern Germany where there are ideal climatic and geographic conditions for the practice of winter sports, such as in the Alpine region or the Black Forest, large tourism flows can be recorded during the winter months. As a result, the actual number of inhabitants during the winter months is significantly higher than during the rest of the year. An example of a town affected by pronounced winter tourism within the study area is the town of Oberstdorf, which is located in the Alpine region and is inhabited by approximately 9000 inhabitants. On average 2.5 million overnight stays and 1.5 million daily tourists are recorded in the town per year (Markt Oberstdorf, 2022). This implies that on average about 6,850 overnight stays per day take place. However, since a large part of these overnight stays takes place during the winter sports season, high water consumption rates are recorded during the winter months, which are partially even higher than the water consumption rates during the summer months. As a result, no clear relationship between the climatic parameters and water consumption can be established and therefore no satisfactory results can be provided for the datasets of water utility companies whose supply area experiences pronounced winter tourism.

Measurement inaccuracies or changes in the supply system

A further interfering factor for the analysis of the water consumption in connection to climate parameters are measurement inaccuracies or changes in the supply structure. While measurement inaccuracies mostly result in sudden peak or base values occurring for a short time, changes in the supply structure most of the time result in long-term increases or decreases in water consumption. These phenomena can occur due to a number of causes, such as incorrect recording of the water consumption, measurement errors due to faulty technology or the addition or elimination of water supplied to large-scale consumers. In some cases, it was possible to remove single occurring extreme data points from the datasets, but in the end, this was not sufficient to achieve a coefficient of determination higher than 0.55, since other interfering factors still influenced the results. As a result, no clear relationship between the climatic parameters and water consumption could be established and therefore no satisfactory results for datasets with measurement inaccuracies or changes in the supply system could be provided.

Of the total 42 analyzed dataset, 27 showed a coefficient of determination that was higher than 0, among which 15 had a coefficient of equal or higher than 0.55, while 15 had a coefficient less than or equal to 0. As described in Chapter 2.4.3 the best possible score a model can reach for the coefficient of determination is 1.0, while a coefficient of determination that equals or is smaller than 0, means that the prediction capacity of the model is either good or worse as the mean value. A coefficient of determination of ≥ 0.55 is considered to be acceptable for a surrogate model. The following table shows the subdivision of the analyzed datasets by climate zone classification:

Table 11 Subdivision of the analyzed datasets based on the values for the coefficient of determination (R^2-values)

Climate zone	analyzed datasets in total	analyzed datasets with R^2-values equal to or higher than 0.55	analyzed datasets with a positive R^2-value lower than 0.55	analyzed datasets with a R^2-value less than or equal to 0
CZ 1	4	1	1	2
CZ 2	5	0	2	3
CZ 3	8	2	4	2
CZ 4	15	4	4	7
CZ 5	10	8	1	1
In total	42	15	12	15

When comparing the results of the different climate zones, it is evident that the number of analyzed datasets that have a coefficient of determination that is positive or greater than 0.55 increases the higher the average annual temperature and the lower the annual precipitation rates within a climate zone is. This confirms previous research showing that the more extreme the prevailing climatic conditions are, the higher their influence on the water consumption is. To all 15 datasets that did not provide a satisfactory result one or more of the listed interfering factors could be assigned to. In total, the 4 determined disruptive factors occurred 25 times within the analyzed datasets. The distribution of the various interfering factors is depicted in the figure below.

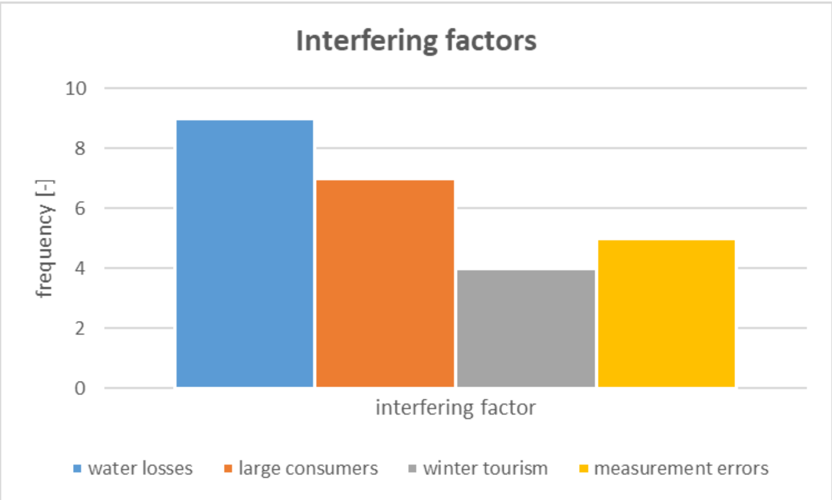


Figure 44 Frequency of the interfering factors

Since some of the datasets did not provide satisfactory results, it was decided to disregard these and to proceed with the remaining 15 datasets with a coefficient of determination of equal to or higher than 0.55. Due to the fact that the data processing and computational time of the individual datasets is very time intensive it was resolved to carry out the calculations with the most promising datasets of the climate zones 1, 3 and 5, the results of which should serve as the basis for a projection of the entire climate zones. The climate zones 2 and 4 should in a further step then be derived from the mean values of the climate zones 1 and 3 as well as 3 and 5, respectively.

3.2.2 Determination of the future water demand

For the determination of the water demand expected in the future, on the one hand the measured data provided by the water utility companies and the weather stations was used, and on the other hand the projected climatic data of the German Weather Service. The projected climatic data is composed of the Representative Concentration Pathways 2.6 and the Representative Concentration Pathways 8.5 (see Figure 17).

This limited the number of parameters to the following six input parameters, which were available for the further analysis:

- The monthly average temperature (x2),
- the monthly precipitation rate (x3),
- the number of hot days per month (x4),
- the number of summer days per month (x5),
- the number of ice days per month (x6),
- the number of the month (x8).

The first five input parameters (x2-x6) are climatic factors, whereas the input parameter x8 is a temporal factor and was added as an additional parameter. The lower number of available parameters, in some cases resulted in a slight decrease of the coefficient of determination, which in most cases was between 0.03 and 0.05. The analysis and calculations were performed individually for each dataset, the results of which are presented in the following chapter.

3.3 Implementation of the risk analysis

3.3.1 Risk identification

In the scope of this thesis the risk identification of the drinking water supply system was dictated by the limitations set within the framework of the thesis. Only hazards and hazardous events that are caused by climate change and that have an impact on the everyday water usage were considered. Extreme events influenced by climate change such as increasing forest fires or floods and their impact on the drinking water supply were not taken into account.

3.3.2 Risk assessment

In the scope of this thesis the risk assessment of the drinking water supply system was performed by determining the likelihood of occurrence, which is set by the two climate scenarios, and the extent of damage, which is defined by the result of the water balance, of the hazards and hazardous events, which were determined during the risk identification.

3.3.2.1 Likelihood of occurrence

In this thesis, the likelihood of occurrence of the hazards and hazardous events was determined by setting two boundary values within which climate change is expected to proceed, a so-called best-case and worst-case scenario (see Chapter 2.2.3). The selection of these two scenarios guarantees that the entire spectrum of possible development options in relation to climate change and its influence on the drinking water demand are being covered.

3.3.2.2 Extent of damage

In this thesis, the extent of damage of a hazard or hazardous event was determined by calculating the difference between the future projected water demand and future water supply. As long as there is a surplus of available water, meaning that the water supply is greater than or equal to the water demand, there is no threat to the security of the supply system and all consumer needs can be met. If the water demand however exceeds the water supply, the needs of the customers cannot be met and there is a risk of a partial or total failure of the water supply system.

3.3.3 Risk management

In the scope of this thesis the risk management of the drinking water supply system was conducted by compiling a catalog of measures in cooperation with the participating water utilities. When selecting the possible measures for the catalog, care was taken to ensure that only measures that the participating water utilities consider to be realistically implementable were included.

3.4 Setting up of the early warning system

For the establishment of the early warning system for the quantitative assessment of drinking water supply systems, the percentage change per decade of the water demand between the 2011-2020 and 2081-2090 was calculated and applied to each decade, which is why the projected graph of water demand is shown as a straight line. In addition, the population forecast of the State Statistical Office was considered in the calculations. Furthermore, the total water demand was split up into its individual components, which are the water demand of the population, the water demand of large-scale consumers, the water demand for own purposes and the water losses. This division was carried out to see how changes of the individual components affect the overall supply situation. Figure 45 represents the interface of the early warning system, with details on the various parameters influencing the water supply and water demand. In this case, the values for water utility 02 are depicted. The water utility company 02 was chosen, since it is located in the climate zone 5, the climate zone which is expected to experience the highest impacts of climate change on the drinking water supply.

Early warning system for the water utiliy company 02		
climatic scenarios		
climate zone of the water utility company	5	
development of the average water demand (RCP2.6):	0.5	%/decade
development of the average water demand (RCP8.5):	1.4	%/decade
development of the maximum water demand (RCP2.6):	0.5	%/decade
development of the maximum water demand (RCP8.5):	2.0	%/decade
water demand of the households		
number of inhabitants (2011-2020):	45,598	C
per capita water consumption (2011-2020):	110	l/(C*d)
population development (2040):	47,903	C
population development (2040):	2.5	%/decade
remaining water demand		
water losses (2011-2020):	223,170	m³/a
	611.0	m³/d
future water losses:	223,170	m³/a
	611.0	m³/d
water demand for own purposes (2011-2020):	150,000	m³/a
	410.7	m³/d
future water demand for own purposes:	150,000	m³/a
	410.7	m³/d
water demand for large-scale consumers (2011-2020):	735,000	m³/a
	2012.3	m³/d
future water demand for large-scale :	735,000	m³/a
	2,012.3	m³/d
peak factor		
daily peak demand factor:	1.8	[-]
future daily peak demand factor:	1.8	[-]
available water supply		
hydrogeological unit of the water utility company	1	
available water supply (own water sources):	157	l/s
	13,582	m³/d
available water supply (long-distance water):	26	l/s
	2,240	m³/d
total available water supply:	183	l/s
	15,822	m³/d
development of the available water supply:	-2.2	%/decade

Figure 45 Interface of the early warning system with the values of the water utility company 02

These values are then used to determine the water demand in each decade and, in addition, the future available water supply. In this case, depending on the climate scenario, this results in the following values, which are listed in Figure 46.

time period	number of inhabitants	available water supply [m^3/d]	RCP2.6					
			per capita water consumption [l/(C*d)]	water demand of inhabitants [m^3/d]	water demand of large-sclae consumers [m^3/d]	water demand for own purposes [m^3/d]	water losses [m^3/d]	total water demand [m^3/d]
2011-2020	45,598	16,613	110	4,998	2,012	411	611	8,032
2021-2030	46,751	16,464	110	5,149	2,012	411	611	8,183
2031-2040	47,903	16,315	111	5,303	2,012	411	611	8,337
2041-2050	49,056	16,169	111	5,458	2,012	411	611	8,492
2051-2060	50,208	16,023	112	5,614	2,012	411	611	8,648
2061-2070	51,361	15,879	112	5,771	2,012	411	611	8,805
2071-2080	52,513	15,736	113	5,930	2,012	411	611	8,964
2081-2090	53,666	15,594	113	6,091	2,012	411	611	9,125

time period	number of inhabitants	available water supply [m^3/d]	RCP8.5					
			per capita water consumption [l/(C*d)]	water demand of inhabitants [m^3/d]	water demand of large-sclae consumers [m^3/d]	water demand for own purposes [m^3/d]	water losses [m^3/d]	total water demand [m^3/d]
2011-2020	45,598	15,822	110	4,998	2,012	411	611	8,032
2021-2030	46,751	15,427	112	5,224	2,012	411	611	8,258
2031-2040	47,903	15,041	114	5,458	2,012	411	611	8,492
2041-2050	49,056	14,665	116	5,699	2,012	411	611	8,733
2051-2060	50,208	14,299	118	5,947	2,012	411	611	8,981
2061-2070	51,361	13,941	121	6,203	2,012	411	611	9,237
2071-2080	52,513	13,593	123	6,466	2,012	411	611	9,500
2081-2090	53,666	13,253	126	6,738	2,012	411	611	9,772

Figure 46 Illustration of the resulting spreadsheet for the entered values in the interface of the early warning system with the values of the water utility company 02

The calculated values for the two climate scenarios are displayed graphically in Chapter 4.3.

4 Results

The results of the analysis and calculations of the water demand in relation to the climatic influences are presented in the following chapter. Although the projections of the water demand are available on a monthly basis, it was decided to present the results as a decadal average. This was done due to the fact that climate projections are primarily used to indicate trends and do not provide accurate forecasts of the future as described in the Chapters 2.2.3 and 3.1.2. Therefore, the projected water demands also cannot provide exact forecasts, but rather serve to point out trends of the water demand in dependence of the projected climate parameters. This approach also contributes to ensure that extreme fluctuations in the projections are evened out. Furthermore, the evaluation of the water demand refers to the gross per capita consumption of drinking water. This means that to calculate the per capita consumption the total drinking water volume supplied by a water utility company is divided by the number of inhabitants connected to the supply system, without excluding charges to large-scale consumers, in the industry or agriculture, water losses and the internal water consumption of the water utility companies. Therefore, in the further course of this thesis the term per capita consumption always refers to the gross per capita consumption of drinking water. Furthermore, the calculations and results assume that the future water demand will continue to develop under today's prevailing consumption patterns, i.e., no change in consumer behavior will take place.

4.1 Projected changes of the climatic parameters in the study area

In the following, the projected changes of the climatic parameters in the climatic zones of the study area are presented briefly. For this purpose, the values of the most negative and most positive climate models of a climate scenario were used. The changes in the climatic parameters in the individual climatic zones are summarized in Figure 47. Comparing the results of Figure 47 with the values of Table 8, it can be seen that the climatic parameters in the scenario RCP2.6 remain almost constant until the decade 2081 - 2090, with only small increases or decreases being observed, whereas significant changes of the climatic parameters in the scenario RCP8.5 can be observed for the same time period.

Average annual values of selected climate parameters in the decade 2081 - 2090											
climate parameter	unit	CZ 1		CZ 2*		CZ 3		CZ 4*		CZ 5	
		RCP2.6	RCP8.5	RCP2.6	RCP8.5	RCP2.6	RCP8.5	RCP2.6	RCP8.5	RCP2.6	RCP8.5
annual mean temperature	[°C]	10.3	12.8	10.3	13.3	10.2	13.7	11.3	14.4	12.4	15.0
hot days	[number]	4	23	8	27	11	30	18	37	24	43
summer days	[number]	37	74	47	83	57	93	67	104	77	114
icy days	[number]	13	7	8	4	4	1	3	1	2	0
annual precipitation rate	[mm/a]	1,262	1,232	978	904	694	575	605	531	515	486

*Figure 47 Projected values of the climatic parameters in the individual climatic zones of the study area in the decade 2081-2090 (*averaged values)*

From the values of Table 8 and Figure 47 the percentage change of climatic parameters per decade in the individual climate zones for the two considered scenarios RCP2.6 and RCP8.5, which is depicted in Figure 48, can be calculated.

Percentage change per decade of the climatic parameters comparing the decades 2011-2020 and 2081-2090										
climate parameter	CZ 1		CZ 2*		CZ 3		CZ 4*		CZ 5	
	RCP2.6	RCP8.5	RCP2.6	RCP8.5	RCP2.6	RCP8.5	RCP2.6	RCP8.5	RCP2.6	RCP8.5
annual mean temperature	5.9%	10.3%	4.5%	8.9%	1.1%	4.9%	1.0%	4.5%	1.4%	4.7%
hot days	-2.7%	47.2%	7.0%	59.6%	-1.5%	20.5%	1.2%	18.1%	3.2%	17.1%
summer days	1.8%	17.9%	7.3%	24.1%	1.9%	12.2%	1.8%	10.5%	2.0%	9.8%
icy days	-5.1%	-9.1%	-7.4%	-10.9%	-10.3%	-13.3%	-11.2%	-13.8%	-12.3%	-14.3%
annual precipitation rate	-2.4%	-2.7%	-3.6%	-4.4%	-3.4%	-5.2%	-2.6%	-4.0%	-1.3%	-2.1%

Figure 48 *Percentage change of the climatic parameters in the individual climatic zones of the study area from the decade 2011-2020 to the decade 2081-2090 (*averaged values)*

According to Figure 48 the strongest percentage changes will take place in the coldest and most precipitation-rich climate zones 1 and 2.

4.2 Projected changes of the supply-related parameters in the study area

In contrast to the climate data, the consumption structure and thus also the consumption data of the individual water utility companies within a climate zone differ greatly. Therefore, for the following section, the percentage change in consumption data for each analyzed water utility company within a climate zone was determined and combined into an overall projection for each climate region. This should allow each water utility company to transfer and apply the projection results independently of their own consumption data. For this purpose, the results of the most optimistic climate model of the climate scenario RCP2.6 were selected as well as the results of the most pessimistic climate model of the climate scenario RCP8.5.

4.2.1 Climate zone 1

Since the water utility company 07 was the only water supplier within climate zone 1 to provide a complete and usable dataset, only its dataset was available to determine the future water demand of the climate zone 1. The changes in the supply parameters of climate zone 1 are depicted in Table 12.

Table 12 *Comparison of the changes in the average per capita water demand and the maximum per capita water demand for the climate scenarios RCP2.6 and RCP8.5 in climate zone 1*

Time period	RCP2.6		RCP8.5	
	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]
2021-2030	1.2	1.0	1.4	1.2
2031-2040	2.1	2.3	2.3	2.7
2041-2050	2.8	3.1	3.1	3.6
2051-2060	3.2	3.2	3.4	4.2
2061-2070	3.0	3.1	3.6	3.5
2071-2080	3.1	3.1	3.8	3.3
2081-2090	3.0	3.0	3.8	3.2

As is evident from Table 12 the change in climatic parameters only has a minor impact on the future water demand. The difference in the average per capita demand between the two analyzed climate scenarios at the end of the study period, in the decade 2081-2090, is only 0.8%. This indicates that the water demand in climate zone 1 is not sensitive to changes in the prevailing climatic conditions. Since the difference between the percent change in maximum per capita demand and average per capita demand is very small, it can be assumed that the peak factor of the water utility companies in climate zone 1 will remain approximately constant.

4.2.2 Climate zone 2

The results of climate zone 2 are derived from the values of climate zones 1 and 3. The changes in the supply parameters of climate zone 2 are depicted in Table 13.

Table 13 Comparison of the changes in the average per capita water demand and the maximum per capita water demand for the climate scenarios RCP2.6 and RCP8.5 in climate zone 2

Time period	RCP2.6		RCP8.5	
	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]
2021-2030	1.4	1.2	1.8	2.4
2031-2040	2.4	2.4	2.9	3.8
2041-2050	3.3	3.2	3.8	4.5
2051-2060	3.5	3.6	4.7	5.2
2061-2070	3.3	3.5	5.2	5.4
2071-2080	3.4	3.4	5.8	5.9
2081-2090	3.3	3.2	6.4	6.3

As is evident from Table 13, the change in climatic parameters has a moderate impact on the future water demand. The difference in the average per capita demand between the two analyzed climate scenarios at the end of the study period, in the decade 2081-2090, is 3.3%. This indicates that the water demand in climate zone 3 is somewhat sensitive to changes in the prevailing climatic conditions. Since the percent change of the maximum per capita demand is larger than the percent change of the average per capita demand, it can be assumed that the peak factor of the water utility companies in climate zone 2 will increase slightly.

4.2.3 Climate Zone 3

To determine the future water demand of climate zone 3, the results of water utilities 04, 10 and 28 B were summarized. The changes in the supply parameters of climate zone 3 are depicted in Table 14.

Table 14 Comparison of the changes in the average per capita water demand and the maximum per capita water demand for the climate scenarios RCP2.6 and RCP8.5 in climate zone 3

Time period	RCP2.6		RCP8.5	
	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]
2021-2030	1.5	1.3	2.1	3.5
2031-2040	2.7	2.5	3.4	4.8
2041-2050	3.8	3.3	4.5	5.3
2051-2060	3.8	3.9	5.9	6.1
2061-2070	3.6	3.8	6.8	7.3
2071-2080	3.6	3.6	7.7	8.4
2081-2090	3.5	3.4	8.9	9.3

As is evident from Table 14, the change in climatic parameters has an elevated impact on the future water demand. The difference in the average per capita demand between the two analyzed climate scenarios at the end of the study period, in the decade 2081-2090, is 5.4%. This indicates that the water demand in climate zone 3 is sensitive to changes in the prevailing climatic conditions. Since the percent change of the maximum per capita demand is larger than the percent change of the average per capita demand, it can be assumed that the peak factor of the water utility companies in climate zone 3 will increase.

4.2.4 Climate zone 4

The results of climate zone 4 are derived from the values of climate zones 3 and 5. The changes in the supply parameters of climate zone 4 are depicted in Table 15.

Table 15 Comparison of the changes in the average per capita water demand and the maximum per capita water demand for the climate scenarios RCP2.6 and RCP8.5 in climate zone 4

Time period	RCP2.6		RCP8.5	
	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]
2021-2030	1.7	1.4	2.7	3.7
2031-2040	2.9	2.6	4.4	5.4
2041-2050	4.2	3.5	6	5.9
2051-2060	4.1	4.1	7.1	7.0
2061-2070	3.9	3.9	8.0	8.7
2071-2080	3.8	3.7	8.7	9.9
2081-2090	3.7	3.5	9.5	11.5

As is evident from Table 15, the change in climatic parameters has a high impact on the future water demand. The difference in the average per capita demand between the two analyzed climate scenarios at the end of the study period, in the decade 2081-2090, is 5.8%. This indicates that the water demand in climate zone 4 is sensitive to changes in the prevailing climatic conditions. Since the percent change of the maximum per capita demand is larger than the percent change of the average per capita demand, it can be assumed that the peak factor of the water utility companies in climate zone 4 will increase.

4.2.5 Climate Zone 5

To determine the future water demand of climate zone 5, the results of water utilities 02, 34 and 24 were summarized. The changes in the supply parameters of climate zone 5 are depicted in Table 16.

Table 16 Comparison of the changes in the average per capita water demand and the maximum per capita water demand for the climate scenarios RCP2.6 and RCP8.5 in climate zone 5

Time period	RCP2.6		RCP8.5	
	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]	Change in the average per capita water demand [%]	Change in the maximum per capita water demand [%]
2021-2030	1.9	1.5	3.3	3.8
2031-2040	3.1	2.7	5.4	5.9
2041-2050	4.5	3.6	7.5	6.5
2051-2060	4.4	4.2	8.3	7.9
2061-2070	4.2	4.0	9.1	10.1
2071-2080	4.0	3.8	9.6	11.4
2081-2090	3.8	3.6	10.0	13.7

As is evident from Table 16, the change in climatic parameters only has a high impact on the future water demand. The difference in the average per capita demand between the two analyzed climate scenarios at the end of the study period, in the decade 2081-2090, is 6.2%. This indicates that the water demand in climate zone 5 is sensitive to changes in the prevailing climatic conditions. Since the percent change of the maximum per capita demand is larger than the percent change of the average per capita demand, it can be assumed that the peak factor of the water utility companies in climate zone 5 will increase.

4.2.6 Overview of the development of the water demand in the investigated Climate Zones

Figure 49 and Figure 50 provide an overview of the decadal change of the average per capita water demand and maximum per capita water demand, respectively.

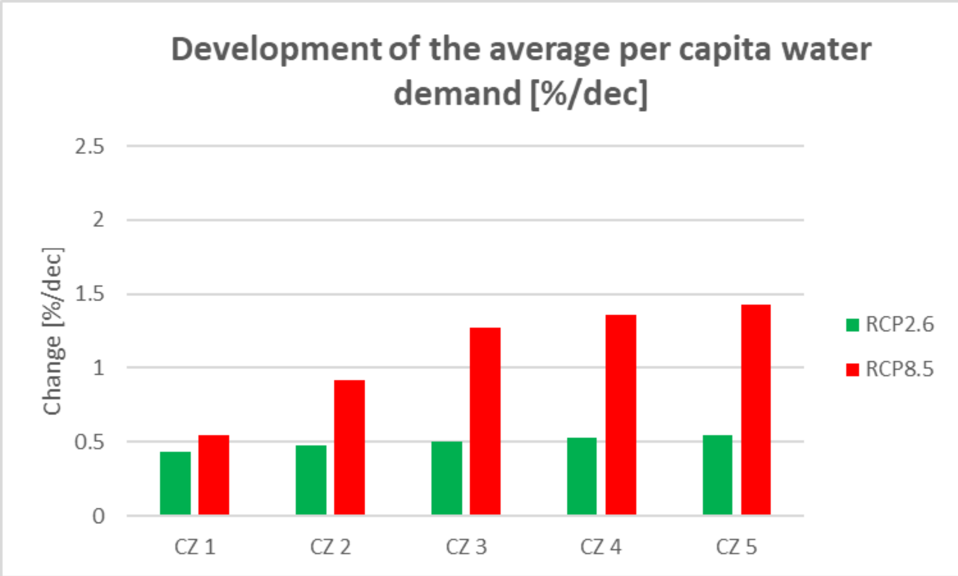


Figure 49 *Overview of the development of the average per capita water demand in all Climate Zones for the climate scenarios RCP2.6 and RCP8.5*

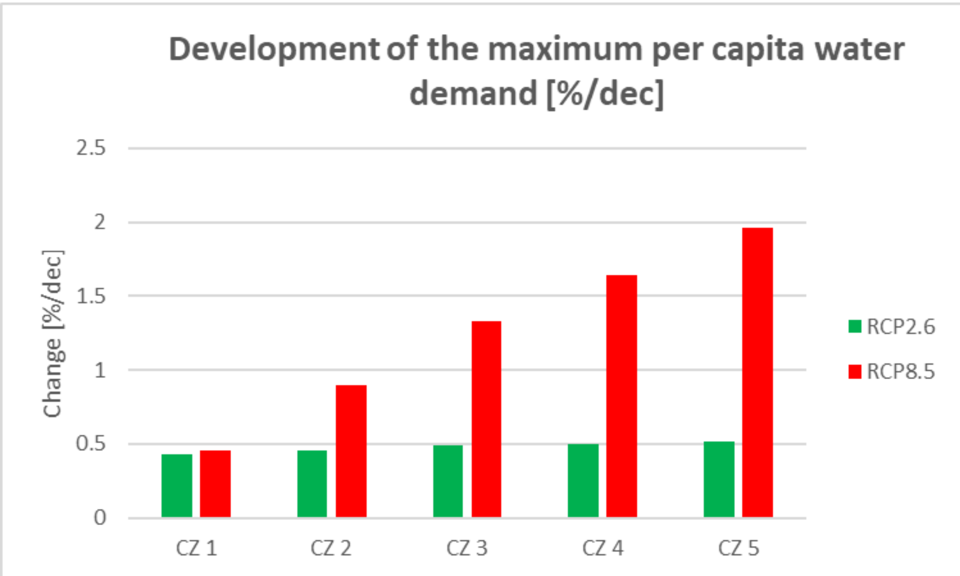


Figure 50 *Overview of the development of the maximum per capita water demand in all Climate Zones for the climate scenarios RCP2.6 and RCP8.5*

When comparing the two bar charts, it is evident that the increase of the average and maximum per capita water demand is nearly identical in the first two climate zones, while the increase in maximum per capita water demand in the last three climates is higher than the increase in the average per capita water demand.

4.3 Demonstration of the functionality of the early warning system

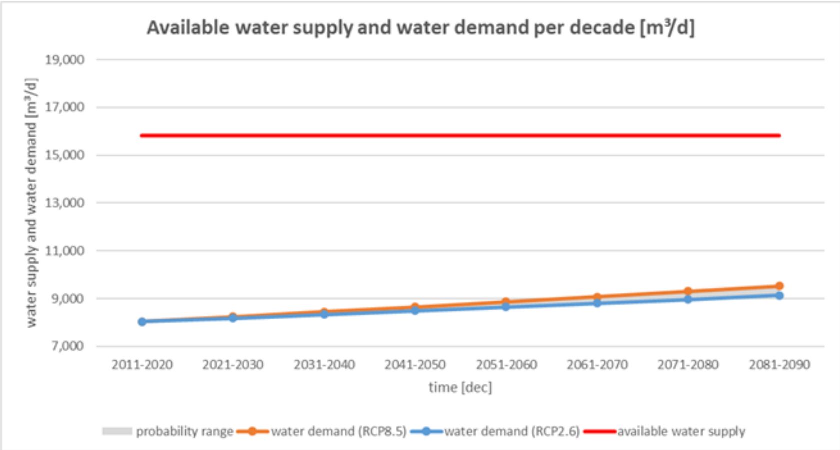
In the following, the implementation of the early warning system is demonstrated on the basis of the data and results of an exemplary selected water supply company, in this case the water utility company 02. This particular water utility company was selected since it is situated in the climate zone 5, the climate zone which is expected to experience the highest impacts of climate change on the drinking water supply. For this purpose, the impacts of the projected changes of the climate parameters on the quantitative water supply, the early warning system itself, as well as possible measures and countermeasures are presented.

4.3.1 Impacts of the projected changes of the climate parameters on the quantitative water supply

As can be seen in Figure 47, depending on the climate scenario a climate-induced increase in water demand of 0.5-1.4% per decade is adopted for the average water demand and an increase of 0.5-2.0% per decade is adopted for the maximum water demand. Since the water utility company 02 is located within the hydrogeologic unit 1, a reduction factor of 5% until 2050 for the well discharge and a reduction factor of 10% until 2050 for the spring discharge is adopted. As the water supplier meets approximately 70% of its water demand from wells and approximately 30% of its water demand from springs, which results in a decrease in the available water supply of 6.5% until 2050. In this depiction, this development is continued in a linear fashion until the year 2090. Furthermore, according to the Federal Statistical Office, a population development of 2.5% per decade is to be expected.

Average daily demand

Figure 51, shows the development of two possible scenarios for the quantitative water supply situation for the average daily demand $Q_{d,m}$ in the future. On the top a scenario is illustrated, in which the water supply remains constant over the study period and on the bottom a scenario is illustrated, in which the water supply decreases by 2.2% per decade over the study period. As can be seen from the figures below, the average daily demand can still be provided even if the water supply decreases by 15.4% until the decade 2081 - 2090.



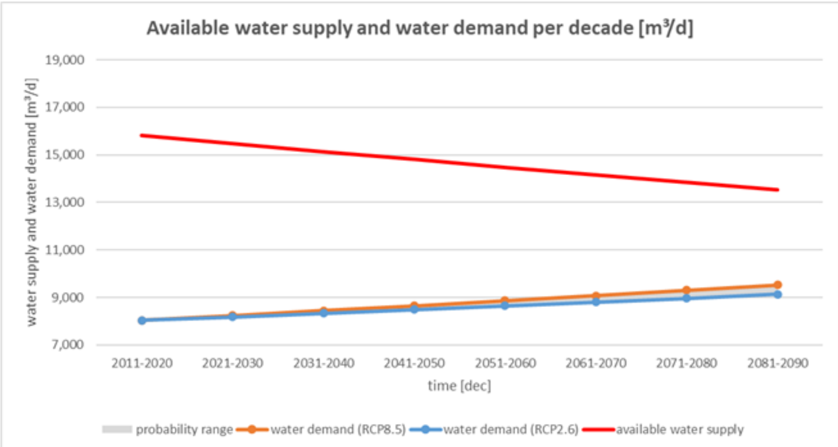


Figure 51 Development of the quantitative drinking water supply situation for the average daily demand assuming a constant water availability (top) and assuming a reduction in the water availability (bottom)

However, since the water supply systems are designed for the peak load so that sufficient water can still be provided even on the day with the highest consumption, the average daily consumption does not pose a challenge for the quantitative water supply in the future. The following analysis therefore focuses on the impact of the projected changes of the climate parameters on the peak daily demand.

Peak daily demand

For the service area of the water utility company 02 a daily peak factor f_d of 1.8 was recorded. Figure 52, shows the development of two possible scenarios for the quantitative water supply situation for the peak daily demand $Q_{d,max}$ in the future. On the top a scenario is illustrated, in which the water supply remains constant over the study period and on the bottom a scenario is illustrated, in which the water supply decreases by 15.4% over the study period.

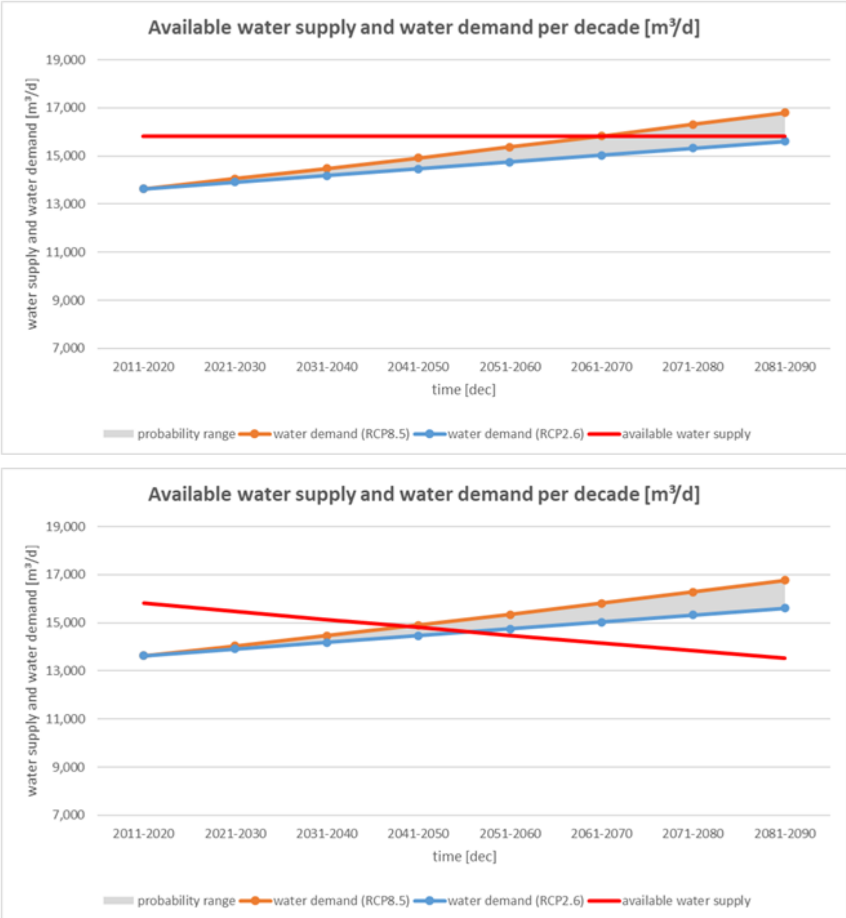


Figure 52 Development of the quantitative drinking water supply situation for the peak daily demand assuming a constant water availability (top) and assuming a reduction in the water availability (bottom)

As can be seen from the top figure above, if the available water supply remains constant, the peak daily demand only can be provided until the decade 2061-2070 for the climate scenario RCP8.5. In the case that the water supply decreases, the intersection of the curves of peak daily demand and available water supply occur before the decade 2041-2050 for the climate scenario RCP8.5 and before the decade 2051-2060 for the climate scenario RCP2.6.

4.3.2 Measures to reduce the impact of the projected changes of the climate parameters on the quantitative water supply

Based on the scenarios presented for the water supply situation during the peak daily demand for the water utility company 02, the implementation of certain measures to optimize the quantitative water supply situation as well as their effects are demonstrated. In Chapter 2.3.3 general risk control measures whose implementation can help to improve the quantitative supply situation of drinking water were already presented. In the following, therefore, the focus will lie on measures which can be implemented by the water utility companies and which implementation they therefore can influence directly.

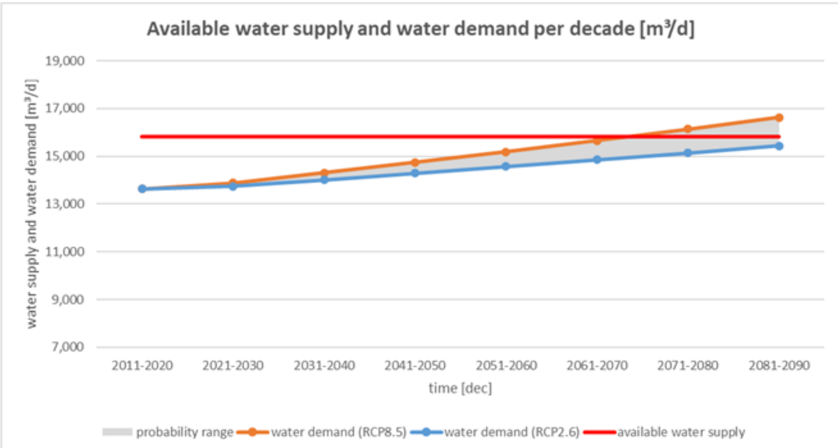
The following measures are considered in the process:

- The minimization of water losses,

- the reduction of the water demand of the large consumers,
- the reduction of the water demand for own purposes,
- the reduction of the peak daily demand and
- the development of new water sources.

Minimization of water losses

With an annual water loss rate of 7.6% of the total volume provided, which corresponds to a total volume of 223,170 m³/a, the water losses of water utility 02 are already relatively low. Therefore, there is only a small potential for savings here. In the following example, a reduction of water losses to a value of 5% of the total volume supplied, which corresponds to a value of 159,407 m³/a, was assumed. In Figure 53, on the top the quantitative supply situation for the case that the water supply remains constant and the water losses are minimized is illustrated, whereas on the bottom the quantitative supply situation for the case that the water supply remains decreases and the water losses are minimized is illustrated.



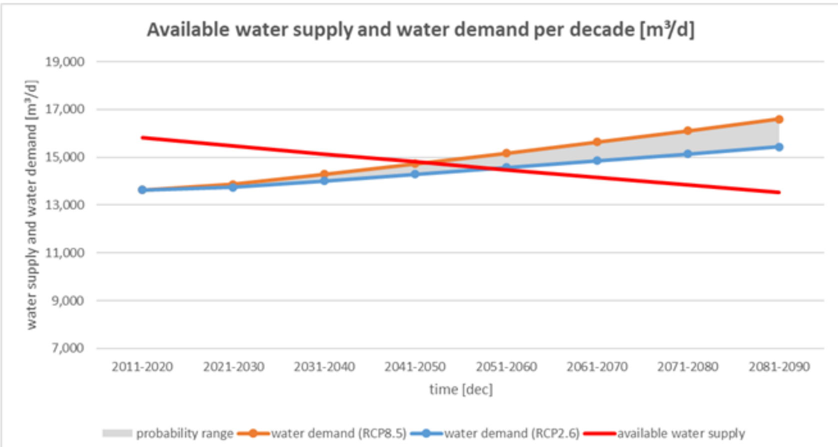


Figure 53 Development of the quantitative drinking water supply situation for the peak daily demand assuming a constant water availability and a reduction of water losses (top) and assuming a reduction in the water availability and a reduction of water losses (bottom)

When comparing the figures above one can notice a minor change in the values for the peak daily demand. Assuming that the available water supply remains constant and the water losses are decreased, the available water supply is sufficient to provide the peak daily demand for approximately a quarter decade longer in both climate scenarios.

Reduction of the water demand of the large consumers

The annual water demand for large-scale consumers amounts to 735,000 m³/a, which corresponds to 25.0% of the total volume provided. Therefore, there is a big potential for savings here. In the following example, a reduction of water losses to a value of 588,000 m³/a, which corresponds to 20.0% of the total volume supplied, was assumed. In Figure 54, on the top the quantitative supply situation for the case that the water supply remains constant and the water demand for large-scale consumers are minimized is illustrated, whereas on the bottom the quantitative supply situation for the case that the water supply remains decreases and the water demand for large-scale consumers are minimized is illustrated.

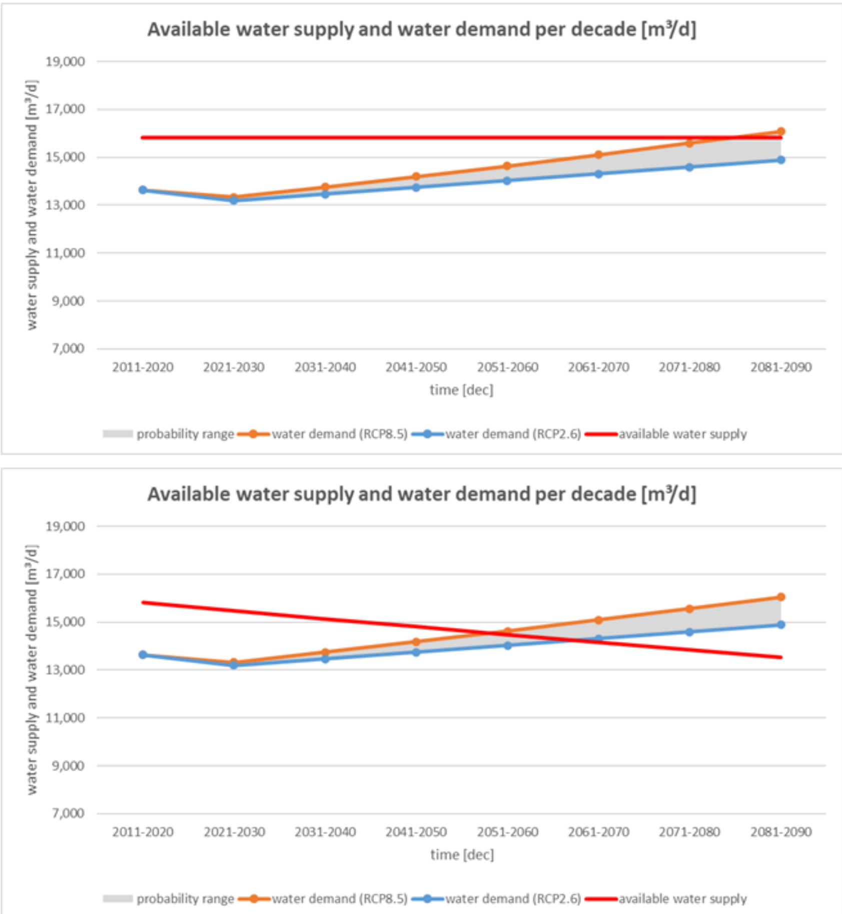


Figure 54 *Development of the quantitative drinking water supply situation for the peak daily demand assuming a constant water availability and a reduction of the water demand for large-scale consumers (top) and assuming a reduction in the water availability and a reduction of the water demand for large-scale consumers (bottom)*

When comparing the figures above one can notice a change in the values for the peak daily demand. Assuming that the available water supply remains constant and the water demand of the large consumers decreases, the available water supply is sufficient to provide the peak daily demand for approximately a decade longer in both climate scenarios.

Reduction of the water demand for own purposes

The annual water demand for own purposes amounts to 150,000 m³/a, which corresponds to 5.1% of the total volume provided. Therefore, there is only a small potential for savings here. In the following example, a reduction of water losses to a value 100,000 m³/a, which corresponds to 3.4% of the total volume supplied, was assumed. In Figure 55, on the top the quantitative supply situation for the case that the water supply remains constant and the water demand for own purposes are minimized is illustrated, whereas on the bottom the quantitative supply situation for the case that the water supply remains decreases and the water demand for own purposes are minimized is illustrated.

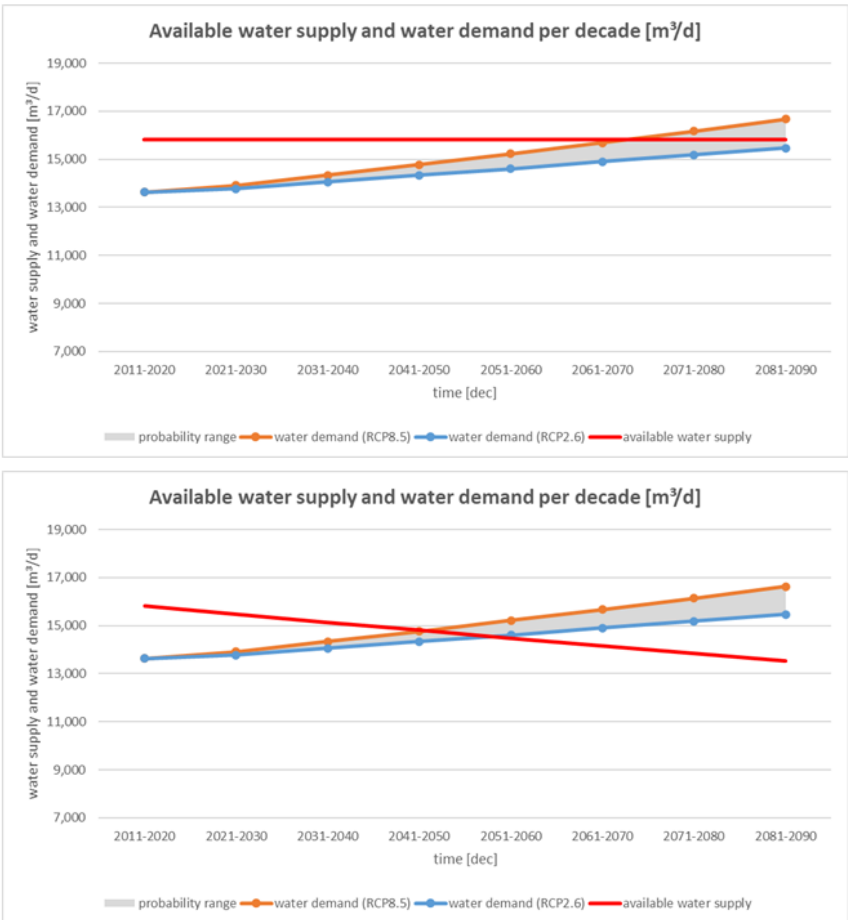


Figure 55 Development of the quantitative drinking water supply situation for the peak daily demand assuming a constant water availability and a reduction of the water demand for own purposes (top) and assuming a reduction in the water availability and a reduction of the water demand for own purposes (bottom)

When comparing the figures above one can notice a minor change in the values for the peak daily demand. Assuming that the available water supply remains constant and the water demand for own purposes decreased, the available water supply is sufficient to provide the peak daily demand for approximately less than a quarter decade longer in both climate scenarios.

Reduction of the daily peak factor

For the service area of the water utility company 02 a daily peak factor of 1.8 was recorded. In the following example, a reduction of daily peak factor to a value of 1.7, was assumed. In Figure 56, on the top the quantitative supply situation for the case that the water supply remains constant and the daily peak factor is reduced is illustrated, whereas on the bottom the quantitative supply situation for the case that the water supply remains decreases and the daily peak demand is reduced is illustrated.

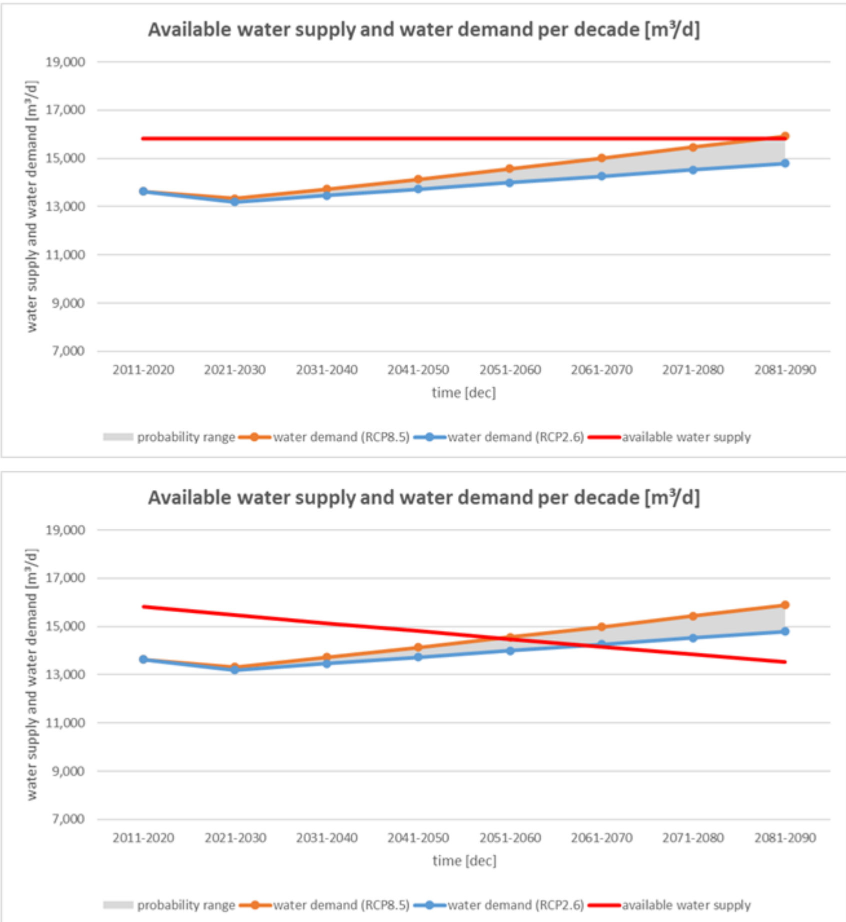
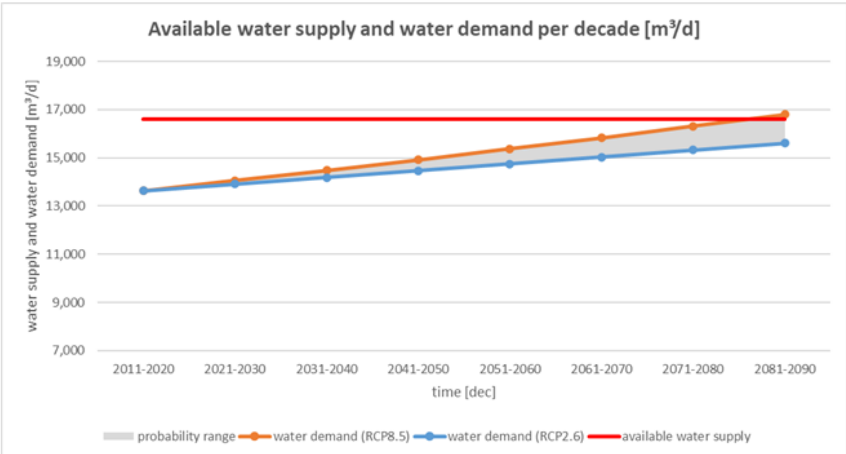


Figure 56 Development of the quantitative drinking water supply situation for the peak daily demand assuming a constant water availability and a reduction of the daily peak factor (top) and assuming a reduction in the water availability and a reduction of the daily peak factor (bottom)

When comparing the figures above one can notice a change in the values for the peak daily demand. Assuming that the available water supply remains constant, and the daily peak factor decreases, the available water supply is sufficient to provide the peak daily demand for approximately one and a quarter decade longer in both climate scenarios.

Development of new water sources

The annually available water supply amounts to 5,775,030 m³/a. In the following example, an increase of the annually available water supply to a value of 6,063,781 m³/a, which corresponds to an increase of 5.0%, was assumed. In Figure 57, on the top the quantitative supply situation for the case that new water sources are developed with no decrease in the water supply taking place of the study period is illustrated, whereas on the bottom the quantitative supply situation for the case that new water sources are developed with decrease in the water supply taking place over the study period is illustrated



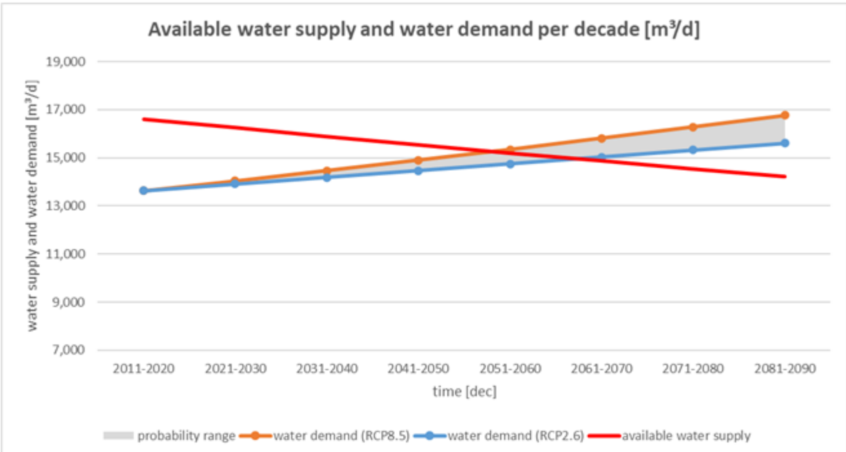


Figure 57 Development of the quantitative drinking water supply situation for the peak daily demand assuming a constant water availability and the development of new water sources (top) and assuming a reduction in the water availability and the development of new water sources (bottom)

When comparing the figures above one can notice a change in the values for the available water supply. Assuming that the available water supply increases, it is sufficient to provide the peak daily demand for approximately one decade longer in both climate scenarios.

Combination of all presented measures

In Figure 58, on the top the quantitative supply situation for the case that the water supply remains constant and the combination of all measures presented is illustrated, whereas on the bottom the quantitative supply situation for the case that the water supply remains decreases and the combination of all measures presented is illustrated.

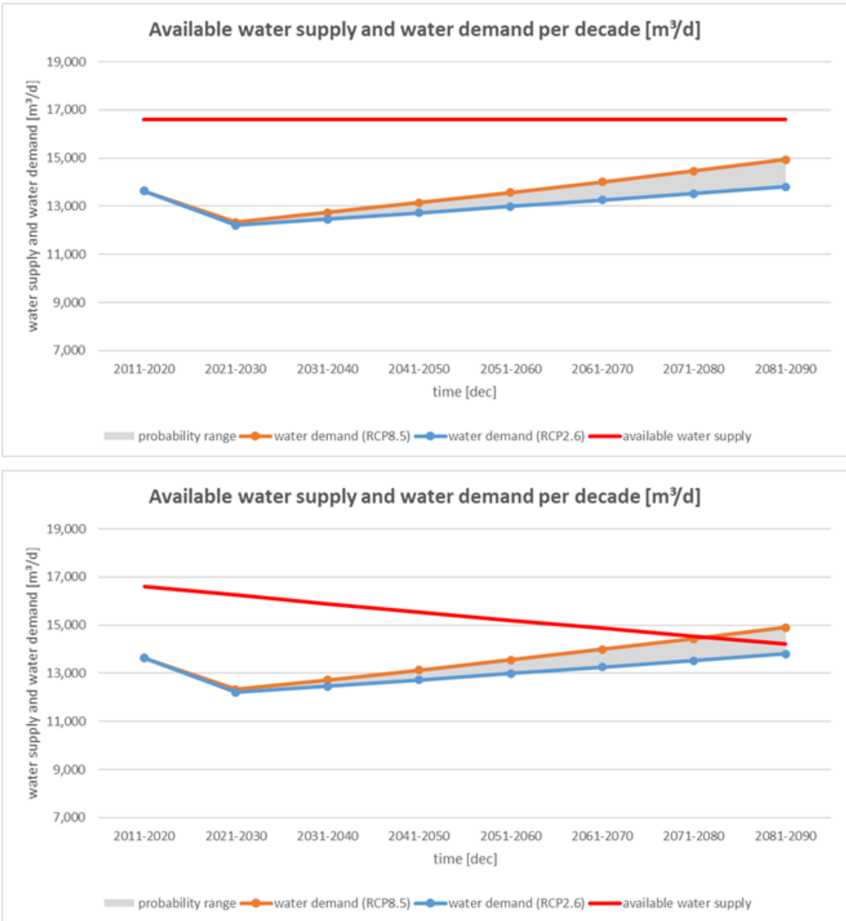


Figure 58 Development of the quantitative drinking water supply situation for the peak daily demand assuming a constant water availability and a implementation of the presented measures (top) and assuming a reduction in the water availability and a implementation of the presented measures (bottom)

Assuming that all measures are implemented, the available water supply is sufficient to provide the peak daily demand approximately two and a half decades longer.

4.4 Measures catalog

Based on the results, a catalog of measures to mitigate impacts of climate change on the quantitative aspects of drinking water supply was developed in cooperation with the surveyed water utility companies. This includes a list of possible measures that the participating water utilities consider to be realistically implementable. The measure catalog can be found in the Appendix C.

5 Conclusion and recommendations

Climate change and its impacts have already led to noticeable changes of the global and regional climatic conditions. Globally, the annual mean temperature in the decade 2010-2020 was already 1.1 °C above the level of the pre-industrial era. In Germany, an increase of 1.9 °C was recorded for the same time period. These developments have led to an increase in droughts in recent years, particularly in the summer months, which in some cases have caused entire rivers and streams to dry up, contributing to crop failures or production stoppages. The drinking water supply has also been and continues to be affected by these changes. Especially hot summers, such as the one in 2018, presented many water utilities in Germany with supply shortages. Climate change and its effects therefore pose major challenges for water utility companies to meet their obligations to continue to provide drinking water of excellent quality in sufficient amounts and with sufficient pressure to the public at all times. In addition to the effects of climate change, there are a number of other challenges facing drinking water supplies in Germany, such as population growth due to migration. As water suppliers only have a limited influence on the aforementioned developments, appropriate countermeasures should be taken at an early stage, especially when considering that many measures cannot be implemented immediately, but must first go through phases of planning, approval and implementation.

In order to be well prepared for the future, it is advisable to conduct a risk analysis in order to investigate to what extent climate change will possibly affect the drinking water supply in future. In theory, the connection between climatic parameters and their impacts on water sources and the drinking water consumption have already been established and characterized. However, statistical and reliable projections of the expected future drinking water demand are missing. Therefore, the aim of this work was to analyze how well the water consumption in Southern Germany can be determined on the basis of climatic factors and in a next step to use climate projections to determine the water demand that can be anticipated in the future. For this purpose, measured climatic and supply-related data from 60 water supply companies in Southern Germany and from weather stations of the German Weather Service, which were collected within the framework of a research project, were analyzed with the help of a surrogate model that is based on a machine learning approach and operates on the basis of Gaussian process regression.

Within this framework, essential knowledge about the possibilities and limitations of the analysis and projection of water demand based on climatic factors were determined. When comparing the individual results of the water utility companies, it became apparent that the more extreme the prevailing climatic conditions in the respective supply area are, the more climate-sensitive the water demand is and thus the accuracy of the water demand projection tends to be more precise. In this context, confounding factors that lead to inaccuracies in the analysis, which include data gaps, measurement inaccuracies, high water losses in the supply system, a high proportion of large-scale consumers and a pronounced water consumption during the winter months caused by winter sport tourism were also identified. The datasets containing confounding factors could not be used for further analysis, which reduced the number of available datasets.

In the next step, projected climate data for two climatic scenarios, a best-case scenario (RCP2.6) and a worst-case scenario (RCP8.5), were requested from the German Weather Service, incorporated into the surrogate model and used to determine the future water demand for each water utility company. The climate scenarios consisted of 20 individual climate models. However, due to time constraints, only 3 climate models per climate scenario were evaluated. The remaining climate models could be used in follow-up studies to corroborate the results obtained in the framework of this thesis. Furthermore, since there no local climate projections exist, the regional climate projection provided by the German Weather Service had to be adapted to the prevailing local climate conditions of the analyzed water utility companies. When local climate projections become available in the future, they should be applied in the analysis, in order to optimize the results from the analysis.

For the purpose of generating a statement about the individual climate zones of the study area, the results of the individual water utility companies of the defined climate zones were merged. Due to time constraints, but also due to a lack of available datasets, three water utilities each from the climate zones 3 and 5 were used for this purpose, while one water utility from climate zone 1 was used. The results of the projections showed that the water demand in the climate zones with high annual precipitation rates and lower annual temperatures, namely the climate zones 1 and 2, are not climate sensitive and therefore climate change will only have a minor influence in these climate zones. The higher the annual temperature and the lower the annual precipitation rate within a climate zone are at present, the more sensitive the water demand reacts to changes of the prevailing climatic conditions and consequently the higher the impact of climate change on the water demand is expected to be. This is apparent, when looking at the calculated results of the climate zones 3 to 5. To validate the results gained in the scope of this thesis, further datasets should be analyzed. For this purpose, additional water utility companies should be surveyed and already available datasets should be further analyzed. The consultancy firm RBS wave GmbH is planning to generate and evaluate further datasets as part of the continuation of the research project.

Subsequently, the results gained from the calculations was used to develop an early warning system as well as a catalog of measures for the water supply companies in the investigated climate zones. The early warning system was designed to allow each water supplier from the study area to identify and visually represent the impact of climate change on their own drinking water system by entering in a few supply-related baseline values. Furthermore, the impact of the implementation of various countermeasures can be ascertained. In addition, the developed early warning system can also be used in meetings with local politicians, committees and decision-makers to highlight the impact of climate change on the local water supply situation and the urgency of the need for action.

In general, limitations in the analysis of the impacts of climate change on the water demand resulted from deficits in the collection, storage and processing of data concerning technical supply parameters in the field of water supply. A solid data basis however is not only crucial for the proper assessment of the future water supply situation with regard to climate change, but also represents the foundation for an optimal supply demand management and decisions regarding the implementation of countermeasures. Therefore, in order to conduct a holistic analysis of the quantitative supply situation with respect to climate change, all relevant water supply parameters, including water consumption rates as well as water levels of wells and spring discharges, should be recorded, analyzed and projected into the future. The therefrom generated results can then be incorporated into the already developed early warning system, which would improve its validity. In addition, considering the security of supply, it is also recommended to record and store the qualitative parameters as well as parameters regarding the continuity of the water supply in order to be able to investigate the impact of climate change on the qualitative and continuous aspects of the drinking water supply at a later stage.

In order to eliminate deficits in the acquisition, storage and processing of data in the water supply sector, it is advisable to conceive and implement a digitization concept. In this context, it is important that the digitization concepts include the recording of all relevant technical supply parameters as well as a selection of suitable measuring intervals. This allows the supply-related parameters to be assigned more precisely to individual weather events as well as to incorporate more climatic parameters, which would lead to an improvement of the accuracy of the calculations and projections. In addition, with a larger amount of data, other machine learning methods, such as artificial neural networks, can be implemented, which in turn can help to improve the accuracy of the projections. Due to time constraints the projected climatic data from 6 climate models were used for the determination of the future water demand. The inclusion of additional climate models could further benefit the accuracy of the water demand projections.

Advances in technology and the associated higher computational power will also allow to determine the influences of individual factors on the climate more precisely. Consequently, this will lead to increasingly more accurate global and regional climate models or enable climate projections for smaller territorial units. The surrogate model developed within the framework of this thesis can incorporate the new findings and thus be constantly updated and further developed.

It should also be mentioned that this thesis has focused on the impact of climate change on the everyday water demand. Extreme events such as increasing forest fires or floods and their impact on the drinking water supply were not taken into account. However, when considering a holistic view of the impact of climate change on the drinking water supply, such extreme weather events and their impacts on the supply system should also be accounted for, so that measures and strategies can be implemented at an early stage to ensure the safety of the drinking water supply at all times.

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Appendix

Appendix A - Results of the input parameter analysis for the individual water supply companies subdivided into the respective climate zones

Climate Zone 1

WUC 01												
Matern-Kernel			Input parameter combination									
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-3.03	-3.03	-1.62	-2.98	-3.20	-3.52	-3.41	-3.46	-3.21
	1.5	once differentiable functions	-3.14	-3.12	-1.62	-2.93	-3.18	-3.55	-3.41	-3.60	-3.28
	2.5	twice differentiable functions	-3.11	-3.15	-1.62	-2.91	-3.18	-3.55	-3.41	-3.63	-3.30
	inf	RBF	-3.02	-3.18	-1.62	-2.88	-3.15	-3.53	-2.81	-3.67	-3.32

best combination:	x3	r2_score:	-1.62

Figure 59 Results of the WUC 01

WUC 07												
Matern-Kernel			Input parameter combination									
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.78	0.71	0.24	0.58	0.32	-0.10	0.52	0.81	0.83
	1.5	once differentiable functions	0.80	0.73	0.24	0.58	0.31	-0.10	0.53	0.82	0.83
	2.5	twice differentiable functions	0.80	0.73	0.24	0.58	0.30	-0.10	0.53	0.82	0.83
	inf	RBF	0.80	0.73	0.24	0.58	0.29	-0.10	0.53	0.81	0.83

best combination:	x3, x4, x6, x7, x8	r2_score:	0.87

Figure 60 Results of the WUC 07

WUC 21												
Matern-Kernel			Input parameter combination									
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	-0.46	-0.33
	1.5	once differentiable functions	-0.39	-0.43	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33
	2.5	twice differentiable functions	-0.33	-0.43	-0.33	-0.33	-0.33	-0.33	-0.33	-0.46	-0.33
	inf	RBF	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	-0.33	-0.46	-0.33

best combination:	x6, x8	r2_score:	-0.31

Figure 61 Results of the WUC 21

WUC 27												
Matern-Kernel			Input parameter combination									
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.03	0.12	-0.05	0.23	-0.04	-0.04	-0.16	0.12	0.14
	1.5	once differentiable functions	0.03	0.14	-0.05	0.24	-0.04	-0.04	-0.16	0.12	0.15
	2.5	twice differentiable functions	0.17	0.15	-0.05	0.24	-0.04	-0.04	-0.04	0.12	0.14
	inf	RBF	0.19	0.16	-0.05	0.24	-0.03	-0.04	-0.04	0.12	0.12

best combination:	x3, x4, x7	r2_score:	0.28

Figure 62 Results of the WUC 27

Climate Zone 2

WVU 08											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.88	-0.89	-0.88	-0.88	-0.88	-0.88	-1.15	-0.88	-0.88
	1.5	once differentiable functions	-0.88	-0.89	-0.88	-0.88	-0.88	-0.88	-1.18	-0.88	-0.88
	2.5	twice differentiable functions	-0.88	-0.88	-0.88	-0.88	-0.88	-0.88	-1.20	-0.88	-0.88
	inf	RBF	-0.93	-0.89	-0.88	-0.88	-0.88	-0.88	-1.23	-0.88	-0.88

best combination:	x3, x5, x7	r2_score:	-0.69

Figure 63 Results of the WUC 08

WUC 25											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.71	-1.22	-1.12	-0.98	-1.30	-1.39	-1.62	-1.00	-0.63
	1.5	once differentiable functions	-0.68	-1.20	-1.09	-1.02	-1.33	-1.23	-1.77	-0.99	-0.65
	2.5	twice differentiable functions	-0.68	-1.20	-1.07	-1.04	-1.35	-1.22	-1.77	-0.99	-0.66
	inf	RBF	-0.68	-1.21	-1.00	-0.90	-1.37	-1.22	-1.77	-0.99	-0.70

best combination:	x6, x7	r2_score:	-0.26

Figure 64 Results of the WUC 25

WUC 42											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.20	-0.16	-0.02	-0.28	-0.60	-0.47	-0.43	-0.09	-0.23
	1.5	once differentiable functions	-0.21	-0.16	-0.02	-0.31	-0.64	-0.37	-0.48	-0.10	-0.21
	2.5	twice differentiable functions	-0.21	-0.17	-0.02	-0.32	-0.64	-0.37	-0.33	-0.10	-0.21
	inf	RBF	-0.21	-0.17	-0.07	-0.32	-0.65	-0.37	-0.32	-0.09	-0.20

best combination:	x3, x5, x8	r2_score:	-0.01

Figure 65 Results of the WUC 42

WVU 47											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.12	-0.12	-0.30	-0.21	-0.12	-0.12	-0.12	-0.12	
	1.5	once differentiable functions	-0.66	-0.12	-0.51	-0.30	-0.12	-0.12	-0.33	-0.12	
	2.5	twice differentiable functions	-0.66	-0.12	-0.57	-0.11	-0.12	-0.12	-0.34	-0.12	
	inf	RBF	-0.66	-0.12	-0.65	-0.08	-0.12	-0.12	-0.30	-0.12	

best combination:	x3, x6	r2_score:	0.2

Figure 66 Results of the WUC 47

WVU 67											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-1.67	-0.02	-0.49	-0.02	-0.02	-0.02	0.08	-0.02	-0.02
	1.5	once differentiable functions	-0.02	-0.02	-0.48	-0.02	-0.02	-0.02	0.08	-0.02	-0.02
	2.5	twice differentiable functions	-0.09	-0.76	-0.49	-0.02	-0.02	-0.02	-0.02	-0.02	-0.10
	inf	RBF	-1.67	-0.02	-0.49	-0.02	-0.02	-0.02	0.08	-0.02	-0.02

best combination:	x3, x7	r2_score:	0.32

Figure 67 Results of the WUC 67

Climate Zone 3

WUC 04											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.35	0.33	0.35	0.41	-0.01	-0.01	0.17	0.24	0.44
	1.5	once differentiable functions	0.35	0.35	0.36	0.42	0.02	0.03	0.11	0.25	0.44
	2.5	twice differentiable functions	0.35	0.35	0.36	0.42	0.02	0.03	0.10	0.25	0.44
	inf	RBF	0.34	0.35	0.36	0.42	0.02	-0.01	0.10	0.25	0.44

best combination:	x1, x3, x6, x7, x8	r2_score:	0.5

Figure 68 Results of the WUC 04

WUC 10											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.25	0.23	0.22	0.31	-0.01	-0.01	0.24	0.29	0.35
	1.5	once differentiable functions	0.27	0.25	0.24	0.31	-0.01	-0.01	0.29	0.29	0.34
	2.5	twice differentiable functions	0.27	0.25	0.24	0.31	-0.01	-0.01	0.29	0.29	0.33
	inf	RBF	0.28	0.26	0.24	0.32	-0.01	-0.01	0.29	0.29	0.33

best combination:	x3, x4, x6, x7	r2_score:	0.4

Figure 69 Results of the WUC 10

WUC 22											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.85	-0.75	-0.61	-1.29	-0.63	-0.63	-0.31	-0.37	-0.30
	1.5	once differentiable functions	-0.85	-0.58	-0.64	-1.46	-0.63	-0.63	-0.39	-0.38	-0.26
	2.5	twice differentiable functions	-0.85	-0.58	-0.64	-1.50	-0.63	-0.65	-0.40	-0.38	-0.26
	inf	RBF	-0.73	-0.60	-0.65	-1.55	-0.63	-0.63	-0.44	-0.39	-0.26

best combination:	x1, x5, x7	r2_score:	-0.04

Figure 70 Results of the WUC 22

WUC 28 A											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.21	-0.19	-0.27	-0.12	-0.16	-0.22	-0.28	-0.28	-0.22
	1.5	once differentiable functions	-0.20	-0.19	-0.28	-0.09	-0.16	-0.22	-0.28	-0.28	-0.23
	2.5	twice differentiable functions	-0.20	-0.19	-0.28	-0.08	-0.16	-0.22	-0.28	-0.28	-0.23
	inf	RBF	-0.19	-0.19	-0.29	-0.08	-0.28	-0.22	-0.28	-0.28	-0.25

best combination:	x4	r2_score:	-0.08

Figure 71 Results of the WUC 28 A

WUC 28 B											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.44	0.43	0.37	0.23	-0.01	-0.11	0.22	0.51	0.66
	1.5	once differentiable functions	0.47	0.46	0.37	0.54	-0.01	-0.11	0.28	0.52	0.64
	2.5	twice differentiable functions	0.47	0.46	0.37	0.04	-0.01	-0.07	0.29	0.52	0.64
	inf	RBF	0.47	0.46	0.36	0.55	-0.01	-0.11	0.29	0.52	0.63

best combination:	x1, x4, x6, x7, x8	r2_score:	0.67

Figure 72 Results of the WUC 28 B

WUC 44											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.12	0.13	-0.22	0.10	0.00	-0.05	0.09	0.39	0.24
	1.5	once differentiable functions	-0.38	0.12	-0.22	0.06	0.00	0.00	0.11	0.39	0.17
	2.5	twice differentiable functions	0.12	0.11	-0.22	0.05	0.00	-0.05	0.12	0.39	0.25
	inf	RBF	0.13	0.10	-0.22	0.20	0.00	0.00	0.14	0.39	0.25

best combination:	x8	r2_score:	0.39

Figure 73 Results of the WUC 44

WUC 65											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.04	-0.03	-0.17	-0.03	-0.02	-0.09	0.07	0.04	-0.03
	1.5	once differentiable functions	-0.05	-0.03	-0.16	-0.04	-0.02	-0.03	0.09	0.04	-0.02
	2.5	twice differentiable functions	-0.06	-0.03	-0.16	-0.04	-0.02	-0.09	0.09	0.04	-0.01
	inf	RBF	-0.02	-0.03	-0.16	-0.05	-0.02	-0.09	0.09	0.04	0.00

best combination:	x5, x7	r2_score:	0.1

Figure 74 Results of the WUC 65

WUC 90											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.23	0.10	0.10	0.12	-0.20	-0.37	-0.06	0.09	0.23
	1.5	once differentiable functions	0.22	0.11	0.12	0.14	-0.22	-0.37	-0.03	0.11	0.27
	2.5	twice differentiable functions	0.21	0.11	0.12	0.16	-0.22	-0.37	-0.02	0.11	0.27
	inf	RBF	0.20	0.11	0.13	0.16	-0.23	-0.37	-0.02	0.11	0.27

best combination:	x1, x3, x7, x8	r2_score:	0.32

Figure 75 Results of the WUC 90

Climate Zone 4

WUC 06											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-2.46	-1.87	-1.53	-1.53	-1.53	-1.69	-1.53	-2.11	-2.39
	1.5	once differentiable functions	-2.56	-1.85	-1.53	-1.74	-1.53	-1.59	-1.53	-2.20	-2.43
	2.5	twice differentiable functions	-2.58	-1.86	-1.53	-1.53	-1.53	-1.60	-1.53	-2.21	-2.43
	inf	RBF	-2.60	-1.87	-1.53	-1.74	-1.53	-1.68	-1.53	-2.21	-2.39

best combination:	x4, x5, x7	r2_score:	-1.38

Figure 76 Results of the WUC 06

WUC 12											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.09	0.05	0.16	0.08	-0.07	-0.07	0.19	0.13	0.20
	1.5	once differentiable functions	0.09	0.07	0.16	0.10	-0.07	-0.07	0.21	0.13	0.18
	2.5	twice differentiable functions	0.00	-0.06	0.15	0.10	-0.07	-0.07	0.21	0.13	0.16
	inf	RBF	0.09	0.07	0.15	0.10	-0.07	-0.07	0.21	0.13	0.22

best combination:	x1, x2, x8	r2_score:	0.29

Figure 77 Results of the WUC 12

WUC 14											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.27	-0.36	-0.31	-0.24	-0.57	-0.62	-0.26	-0.38	-0.29
	1.5	once differentiable functions	-0.28	-0.34	-0.27	-0.21	-0.57	-0.57	-0.25	-0.57	-0.26
	2.5	twice differentiable functions	-0.28	-0.34	-0.27	-0.20	-0.57	-0.57	-0.26	-0.38	-0.26
	inf	RBF	-0.29	-0.34	-0.27	-0.20	-0.57	-0.57	-0.26	-0.38	-0.25

best combination:	x1, x7	r2_score:	-0.18

Figure 78 Results of the WUC 14

WUC 16											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.13	0.07	-0.06	0.22	-0.06	-0.06	0.14	-0.06	-0.06
	1.5	once differentiable functions	0.18	0.16	-0.06	0.22	-0.06	-0.06	0.21	-0.06	0.14
	2.5	twice differentiable functions	0.19	0.18	0.02	0.22	-0.06	-0.06	0.23	-0.06	0.19
	inf	RBF	0.20	0.20	0.01	0.22	-0.06	-0.06	0.24	-0.06	0.23

best combination:	x2, x3, x7	r2_score:	0.31

Figure 79 Results of the WUC 16

WUC 26											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-1.84	-1.82	-1.74	-1.75	-2.21	-2.21	-1.51	-1.92	-1.54
	1.5	once differentiable functions	-1.93	-1.84	-1.69	-1.72	-2.21	-2.21	-1.45	-1.92	-1.55
	2.5	twice differentiable functions	-1.88	-1.84	-1.69	-1.72	-2.21	-2.21	-1.45	-1.92	-1.51
	inf	RBF	-1.88	-1.84	-1.68	-1.72	-2.21	-2.21	-1.44	-1.93	-1.52

best combination:	x7, x8	r2_score:	-1.38

Figure 80 Results of the WUC 26

WUC 31											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.54	0.45	0.21	0.42	-0.05	-0.17	0.44	0.45	0.64
	1.5	once differentiable functions	0.53	0.47	0.19	0.42	-0.05	-0.18	0.45	0.45	0.65
	2.5	twice differentiable functions	0.53	0.47	0.17	0.41	-0.05	-0.17	0.45	0.44	0.60
	inf	RBF	0.48	0.46	0.36	0.44	-0.11	-0.18	0.45	0.44	0.58

best combination:	x1, x6, x7	r2_score:	0.73

Figure 81 Results of the WUC 31

WUC 32											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.12	0.14	-0.03	0.10	-0.48	-0.57	0.18	0.09	0.36
	1.5	once differentiable functions	0.17	0.13	-0.01	0.04	-0.48	-0.58	0.18	0.09	0.35
	2.5	twice differentiable functions	0.18	0.13	-0.02	0.02	-0.48	-0.53	0.18	0.09	0.35
	inf	RBF	0.21	0.13	0.09	0.17	-0.53	-0.53	0.17	0.09	0.34

best combination:	x5, x6, x7, x8	r2_score:	0.51

Figure 82 Results of the WUC 32

WUC 50											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.65	-0.70	-0.67	-0.64	-0.93	-0.89	-0.51	-0.73	-0.55
	1.5	once differentiable functions	-0.62	-0.68	-0.64	-0.60	-0.94	-0.90	-0.53	-0.73	-0.53
	2.5	twice differentiable functions	-0.63	-0.68	-0.63	-0.59	-0.94	-0.90	-0.51	-0.73	-0.53
	inf	RBF	-0.64	-0.68	-0.63	-0.59	-0.95	-0.94	-0.51	-0.74	-0.54

best combination:	x7, x8	r2_score:	-0.51

Figure 83 Results of the WUC 50

WUC 55											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.14	0.09	0.12	0.11	-0.09	-0.18	0.10	0.06	0.14
	1.5	once differentiable functions	0.16	0.10	0.13	0.13	-0.09	-0.20	0.11	0.07	0.15
	2.5	twice differentiable functions	0.16	0.10	0.13	0.13	-0.09	-0.20	0.11	0.07	0.14
	inf	RBF	0.12	0.10	0.14	0.13	-0.09	-0.09	0.09	0.07	0.12

best combination:	x1, x3, x7	r2_score:	0.22

Figure 84 Results of the WUC 55

WUC 63											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.16	-0.15	-0.18	-0.16	-0.26	-0.26	-0.26	-0.13	-0.09
	1.5	once differentiable functions	-0.18	-0.15	-0.16	-0.16	-0.26	-0.28	-0.26	-0.12	-0.09
	2.5	twice differentiable functions	-0.19	-0.15	-0.16	-0.16	-0.26	-0.28	-0.24	-0.12	-0.09
	inf	RBF	-0.13	-0.14	-0.16	-0.16	-0.26	-0.28	-0.20	-0.13	-0.09

best combination:	x6, x7	r2_score:	-0.02

Figure 85 Results of the WUC 63

WUC 69											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.23	-0.20	-0.27	-0.35	-0.34	-0.27	-0.11	-0.13	-0.09
	1.5	once differentiable functions	-0.28	-0.23	-0.27	-0.37	-0.34	-0.27	-0.08	-0.13	-0.09
	2.5	twice differentiable functions	-0.28	-0.19	-0.27	-0.37	-0.34	-0.27	-0.07	-0.13	-0.09
	inf	RBF	-0.30	-0.18	-0.18	-0.18	-0.27	-0.25	-0.07	-0.13	-0.09

best combination:	x3, x7, x8	r2_score:	-0.04

Figure 86 Results of the WUC 69

WUC 70											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.06	0.06	0.16	-0.01	-0.03	-0.08	0.12	0.25	0.14
	1.5	once differentiable functions	-0.07	0.07	0.15	-0.02	-0.04	-0.09	0.12	0.25	0.16
	2.5	twice differentiable functions	0.00	0.10	0.15	-0.02	-0.04	-0.09	0.12	0.25	0.17
	inf	RBF	0.03	0.10	0.16	0.04	-0.03	-0.10	0.12	0.24	0.15

best combination:	x2, x3, x8	r2_score:	0.32

Figure 87 Results of the WUC 70

WUC 77											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.62	0.50	0.24	0.56	-0.01	-0.32	0.37	0.63	0.67
	1.5	once differentiable functions	0.64	0.52	0.25	0.56	0.00	-0.32	0.37	0.63	0.68
	2.5	twice differentiable functions	0.64	0.53	0.25	0.57	0.00	-0.32	0.38	0.63	0.68
	inf	RBF	0.64	0.53	0.25	0.57	0.00	-0.32	0.37	0.63	0.67

best combination:	x6, x7, x8	r2_score:	0.76

Figure 88 Results of the WUC 77

WUC 79											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.26	0.31	0.14	0.27	-0.12	-0.18	0.26	0.25	0.34
	1.5	once differentiable functions	0.28	0.32	0.15	0.28	-0.12	-0.18	0.33	0.26	0.35
	2.5	twice differentiable functions	0.28	0.33	0.15	0.29	-0.12	-0.18	0.34	0.27	0.35
	inf	RBF	0.28	0.33	0.14	0.29	-0.18	-0.18	0.34	0.27	0.35

best combination:	x6, x7	r2_score:	0.46

Figure 89 Results of the WUC 79

WUC 86											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.15	-0.20	-0.10	-0.13	-0.36	-0.34	-0.09	-0.27	-0.12
	1.5	once differentiable functions	-0.14	-0.20	-0.08	-0.11	-0.36	-0.34	-0.07	-0.25	-0.13
	2.5	twice differentiable functions	-0.14	-0.20	-0.08	-0.10	-0.38	-0.34	-0.07	-0.25	-0.13
	inf	RBF	-0.14	-0.20	-0.07	-0.10	-0.38	-0.34	-0.06	-0.25	-0.14

best combination:	x2, x3, x6, x7	r2_score:	0

Figure 90 Results of the WUC 86

Climate Zone 5

WUC 02											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.55	0.56	0.56	0.48	-0.04	0.10	0.65	0.42	0.67
	1.5	once differentiable functions	0.55	0.56	0.45	0.54	-0.04	0.11	0.64	0.42	0.69
	2.5	twice differentiable functions	0.55	0.56	0.10	0.54	-0.04	-0.06	0.64	0.42	0.68
	inf	RBF	0.55	0.56	0.10	0.54	-0.04	0.12	0.65	0.42	0.68

best combination:	x2, x3, x6, x7	r2_score:	0.73

Figure 91 Results of the WUC 02

WUC 15											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.68	0.71	0.65	0.66	0.08	0.00	0.69	0.60	0.78
	1.5	once differentiable functions	0.70	0.69	0.65	0.65	0.08	0.00	0.72	0.61	0.81
	2.5	twice differentiable functions	0.70	0.69	0.65	0.65	0.02	0.00	0.73	0.61	0.81
	inf	RBF	0.68	0.69	0.63	0.65	0.08	0.00	0.73	0.60	0.81

best combination:	x1, x3, x4, x7	r2_score:	0.86

Figure 92 Results of the WUC 15

WUC 17											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.09	-0.10	0.10	0.07	-0.13	-0.35	-0.05	0.08	0.06
	1.5	once differentiable functions	0.11	-0.10	0.06	0.10	-0.13	-0.35	-0.04	0.10	0.08
	2.5	twice differentiable functions	0.11	-0.10	0.04	0.11	-0.13	-0.24	-0.04	0.10	0.09
	inf	RBF	0.11	-0.12	0.02	0.11	-0.13	-0.35	-0.05	0.11	0.08

best combination:	x1, x8	r2_score:	0.14

Figure 93 Results of the WUC 17

WUC 24											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.72	0.72	0.60	0.67	0.07	-0.08	0.79	0.61	0.86
	1.5	once differentiable functions	0.72	0.72	0.57	0.68	0.07	-0.08	0.80	0.61	0.85
	2.5	twice differentiable functions	0.71	0.71	0.59	0.68	0.07	-0.08	0.79	0.61	0.84
	inf	RBF	0.69	0.71	0.59	0.66	0.07	-0.08	0.79	0.61	0.83

best combination:	x2, x3, x6, x7	r2_score:	0.88

Figure 94 Results of the WUC 24

WUC 30											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.48	0.45	0.36	0.39	0.00	-0.02	0.28	0.37	0.41
	1.5	once differentiable functions	0.49	0.44	0.36	0.38	0.01	0.00	0.29	0.37	0.43
	2.5	twice differentiable functions	0.49	0.44	0.36	0.38	0.01	-0.02	0.29	0.37	0.43
	inf	RBF	0.41	0.42	0.36	0.38	0.00	-0.02	0.29	0.37	0.44

best combination:	x1, x2, x3, x4, x5, x7, x8	r2_score:	0.48

Figure 95 Results of the WUC 30

WUC 33											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.52	0.60	0.47	0.56	-0.08	-0.25	0.72	0.42	0.75
	1.5	once differentiable functions	0.53	0.57	0.43	0.57	-0.09	-0.25	0.73	0.43	0.75
	2.5	twice differentiable functions	0.52	0.57	0.43	0.56	-0.09	-0.25	0.73	0.43	0.74
	inf	RBF	0.52	0.57	0.41	0.55	-0.09	-0.25	0.73	0.43	0.74

best combination:	x1, x3, x7	r2_score:	0.79

Figure 96 Results of the WUC 33

WUC 34											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.54	0.32	0.40	0.52	-0.16	-0.30	0.47	0.33	0.57
	1.5	once differentiable functions	0.55	0.32	0.41	0.42	-0.16	-0.29	0.47	0.34	0.60
	2.5	twice differentiable functions	0.55	0.32	0.42	0.57	-0.16	-0.29	0.48	0.34	0.61
	inf	RBF	0.54	0.31	0.42	0.15	-0.16	-0.29	0.48	0.34	0.61

best combination:	x1, x2, x3, x6, x7	r2_score:	0.65

Figure 97 Results of the WUC 34

WUC 35											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	-0.75	-0.75	-0.82	-0.68	-0.75	-0.80	-0.40	-0.43	-0.42
	1.5	once differentiable functions	-0.76	-0.71	-0.82	-0.80	-0.75	-0.79	-0.34	-0.45	-0.40
	2.5	twice differentiable functions	-0.75	-0.71	-0.75	-0.62	-0.75	-0.79	-0.33	-0.45	-0.40
	inf	RBF	-0.76	-0.74	-0.82	-0.61	-0.75	-0.87	-0.33	-0.47	-0.39

best combination:	x1, x3, x6, x7	r2_score:	-0.15

Figure 98 Results of the WUC 35

WUC 37											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.47	0.39	0.38	0.44	-0.11	-0.10	0.53	0.31	0.55
	1.5	once differentiable functions	0.45	0.37	0.38	0.45	-0.11	-0.11	0.53	0.32	0.53
	2.5	twice differentiable functions	0.44	0.37	0.38	0.45	-0.11	-0.11	0.53	0.32	0.52
	inf	RBF	0.43	0.37	0.38	0.46	-0.07	-0.11	0.52	0.32	0.52

best combination:	x1, x3, x6, x7	r2_score:	0.57

Figure 99 Results of the WUC 37

WUC 75											
Matern-Kernel			Input parameter combination								
			x1	x2	x3	x4	x5	x6	x7	x8	combination
			average T.	Max. T.	HD	SD	ID	P	CWB	monthly. N.	
nu-value	0.5	absolute exponential	0.26	0.26	0.20	0.30	-0.22	-0.41	0.46	0.22	0.48
	1.5	once differentiable functions	0.27	0.28	0.14	0.30	-0.23	-0.39	0.49	0.23	0.51
	2.5	twice differentiable functions	0.26	0.28	0.18	0.29	-0.23	-0.41	0.49	0.23	0.52
	inf	RBF	0.26	0.28	0.17	0.29	-0.23	-0.41	0.50	0.22	0.51

best combination:	x1, x2, x4, x6, x7	r2_score:	0.55

Figure 100 Results of the WUC 75

Appendix B - Development of the climatic parameters for the supply area of one investigated individual water utility companies from the climate zone 5

In the following, the development of the prognosticated climatic parameters for one water utility company, in this case the WUC 02 located in the climate zone 5, are illustrated exemplarily.

WUC 02:

Table 17 Development of the decadal average precipitation rate for the water utility company 02 in the period 2011-2090

Decadal precipitation rate [°C]						
time period	RCP2.6			RCP8.5		
	(1)	(2)	(3)	(1)	(2)	(3)
2011-2020	731	731	731	731	731	731
2021-2030	694	682	696	667	637	693
2031-2040	696	677	696	799	641	642
2041-2050	686	641	649	731	698	664
2051-2060	676	705	746	718	658	650
2061-2070	681	659	764	775	638	626
2071-2080	687	704	616	811	674	672
2081-2090	691	694	766	781	650	631

Table 18 Development of the number of summer days per decade for the water utility company 02 in the period 2011-2090

Decadal number of summer days [-]						
time period	RCP2.6			RCP8.5		
	(1)	(2)	(3)	(1)	(2)	(3)
2011-2020	613	613	613	613	613	613
2021-2030	613	615	614	686	663	651
2031-2040	612	614	613	725	703	696
2041-2050	610	612	613	755	734	728
2051-2060	609	612	612	827	798	789
2061-2070	609	610	611	856	731	717
2071-2080	607	611	610	901	869	850
2081-2090	605	611	609	972	948	932

Table 19 Development of the number of hot days for the water utility company 02 in the period 2011-2090

Decadal number of hot days [-]						
time period	RCP2.6			RCP8.5		
	(1)	(2)	(3)	(1)	(2)	(3)
2011-2020	161	161	161	161	161	161
2021-2030	156	161	159	172	169	165
2031-2040	155	162	158	184	176	172
2041-2050	154	163	158	191	183	179
2051-2060	154	162	157	207	190	185
2061-2070	153	161	155	214	197	191
2071-2080	151	160	154	223	208	199
2081-2090	150	160	153	241	237	218

Table 20 Development of the number of icy days for the water utility company 02 in the period 2011-2090

Decadal number of icy days [-]						
time period	RCP2.6			RCP8.5		
	(1)	(2)	(3)	(1)	(2)	(3)
2011-2020	77	77	77	77	77	77
2021-2030	71	76	73	69	55	42
2031-2040	56	63	59	44	35	28
2041-2050	47	55	51	36	23	16
2051-2060	34	42	38	24	17	8
2061-2070	14	26	21	9	11	4
2071-2080	8	20	13	7	4	2
2081-2090	2	11	6	3	1	0

Appendix C - Measure catalog

This brief measure catalog was compiled together with the water utility companies participating in the research project “Influence of climate change on drinking water supply” and includes measures that the water suppliers considered to be realistically implementable. The measure catalog should serve a guide for water utility companies in the study area, whose water supply is at risk due to climate change and who therefore need to take action to ensure a secure water supply can be provided in the future. The catalog of measures is intended only as a suggestion, the implementation and feasibility must be examined individually in the respective supply area. The measures are divided into 2 categories. On the one hand, measures that reduce the water demand and on the other hand, measures that increase the available water supply. It should be noted that the measures that reduce the water demand are preferable to the measures that increase the water supply.

<u>Measures to reduce the water demand</u>

1. Measures to minimize water losses

   It should be investigated whether the water demand can be reduced by minimizing water losses. How high are the water losses? Are there approaches in place to detect pipe bursts and to minimize water losses?

2. Measures to reduce the water demand of large consumers

   It should be investigated whether the water demand can be reduced by reducing the water demand of large consumers. Is it possible for the large consumers to reduce their consumption or to be supplied by other sources?

3. Measures to reduce the water demand for own purposes

   It should be investigated whether the water demand can be reduced by reducing the water demand for own purposes. Is it possible to reduce their consumption or to provide the water consumed for own purposes by other sources?

4. Measures to reduce the peak daily demand

   It should be investigated whether the water demand can be reduced by reducing the peak daily demand. Is it possible to reduce the peak daily factor?

5. Measures to inform the public

   It should be investigated whether the water demand can be reduced by conducting programs aimed to inform the public about water conservation. Are there information campaigns already?

6. Change of the water pricing

It should be investigated whether the current water pricing can be modified. Has any thought been given to a new pricing system? Can a new pricing system be implemented?

7. Promotion of water-saving measures in the household

It should be investigated whether the promotion of water-saving measures in the household can be implemented. Is it possible to promote water-saving fittings or systems for rain storage and usage?

<u>Measures to increase the available water supply</u>

1. Development of new water sources

It should be investigated whether the water supply can be increased by water from own sources or by one or more connection(s) to long-distance water supplier(s).

<u>Measures to increase the available water supply</u>

1. Development of new water sources

It should be investigated whether the water supply can be increased by water from own sources or by one or more connection(s) to long-distance water supplier(s).

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