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March 24, 2025

Preface

Presented before you is my bachelor thesis with the title: “The Impact of Climate Change on the Hydrology of the Wien River and the Implications for Flooding of the Adjacent U4 Subway Line”. During my Bachelor’s in Civil Engineering, I learned about a wide range of topics, but hydrology has been my main area of interest. With climate change effects being of growing significance, researching its impact on a river seemed like a meaningful and interesting choice to write my thesis about.

Writing this thesis has learned me a lot about using a hydrological model. It also expanded my programming skills and challenged me to critically assess data and results.

I would like to thank dr. ir. Rolf Hut and ir. Vincent Hoogelander for their excellent guidance throughout my research. Your support with helping me narrow down my topic, structure my research and critically evaluate my results has been of great importance. I would like to thank ir. Mark Melotto as well for helping me with issues concerning the eWaterCycle platform. Additionally, I would like to thank Lars Kramer, for providing me with peer feedback.

My hope for this research is that it will contribute to a broader understanding of the impact of climate change on rivers. Furthermore, I aim to provide the city of Vienna with recommendations on whether or not their flood protection infrastructure for the U4 Subway Line will need improvements.

I hope you find this thesis an interesting read.

Thirza van Esch Delft, 31-3-2025

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Abstract

Hier komt de abstracttekst…

1 Introduction

1.1 Motivation

Last September, the Wien River, normally a small trickle, swelled into a raging torrent, having a serious impact on public transport. Damage to the public transport was kept to a minimum thanks to the flood alarm plan, but still almost one-million litres of water had to be pumped out of the subway lines (Krone.At, 2024b).

The Wien River is one of the largest rivers of Vienna and has a catchment area of 230 km2. Along a reach of over 8 km, the subway line U4 follows the river in an open section on the right bank. Flooding on the Wien River is critical due to its rapid onset and potential for severe damage. The large area of impervious surfaces in the catchment area make Wien River floodings typically flash floodings. The threat regarding flooding in Vienna is caused by large channel slopes and flow velocities, rapid increase of discharge and the absence of natural retention areas. Furthermore, the low hills and mountains in the area intensify storm events compared to plain areas through intensified convective air movement (Compton et al., 2009, pp. 13–14).

Dore (2005) states in his article about climate change and changes in global precipitation patterns that due to climate change, precipitation is expected to increase in the Northern Hemisphere. The wet areas will get wetter, and the rainfall will get more intense. Changes in precipitation due to climate change may affect the water level and discharge of the Wien River, posing potential risks to the operation and safety of the adjacent U4 subway line.

1.2 Problem Analysis

Flood risk management is critical for urban resilience, especially in places where natural waters are closely linked to infrastructure. Compton et al. (2009) highlight in their study on uncertainty and disaster risk management how an approach based on catastrophe modelling can provide a useful framework for comparing different mitigation strategies as well as integrate the risk perspectives of different technical disciplines. For their study they use hydraulic models to obtain probability of failure for different storm return periods and states of the flood control reservoirs.

This report will focus on flood risk as well but shifts the focus towards how the discharge and water levels in the Wien River will change due to climate change, influencing the flood risk for the U4 subway line. A Hydrological model forced with different climate change scenarios will be implemented to simulate the future discharge scenarios of the Wien River. The report will focus solely on changes in flood frequency due to climate change and excludes the current flood protection infrastructures and adaption measures these might require.

This research will contribute to Vienna's flood risk management and is relevant for the transportation authorities, policymakers and urban developers in Vienna who are seeking to make the city future-proof for increasing threats due to climate change.

1.3 Objective

In this report the following research question will be answered: "What is the impact of predicted climate change on the hydrology of the Wien River and what are the implications for flooding of the adjacent U4 subway line?" This is done using the following sub-questions:

- What is the current maximum discharge (m3/s) in the Wien above which the U4 subway line will flood?
- How often does the discharge currently exceed the maximum?
- How often will the discharge exceed this maximum in the future under different climate change

scenarios?

1.4 Approach

To determine the maximum discharge threshold for flooding of the U4, literature study needs to be done. Historical events, flood risk maps, research papers and monitoring stations need to be analysed.
The current frequency at which the discharge exceeds this maximum can be determined using eWaterCycle. Past streamflow can be simulated with a hydrological model. The simulated discharge data then can be compared to the flood threshold determined before. The model should be calibrated using real-world data. The frequency of flooding of the U4 with current discharge data can be conducted with return period calculations.
The future discharge can be simulated with the use of future climate projections. Climate models provided by CMIP6 will be used. Different IPCC scenarios give different projected climate variables which can be used in hydrological models using eWaterCycle to simulate future discharge. These modelled future discharge scenarios should be compared to the flood threshold to estimate the future frequency of exceedance for different climate change scenarios.

For this research I will use a model through the eWaterCycle platform. The eWaterCycle platform provides the hydrological community with models that can all be accessed in a similar manner, through the Jupyter notebook environment in eWaterCycle.

1.5 Reading Guide

In Chapter 2 the current maximum discharge (m3/s) is determined above which the U4 subway line will flood. Chapter 3 determines how often the discharge currently exceeds this maximum using the observation data from eWaterCycle. In Chapter 4 the hydrological model is chosen and calibrated. In Chapter 5 different climate change scenarios are projected in hydrological models to simulate future discharge. These future discharge scenarios are compared to the flood threshold to estimate the future flooding frequency of the U4 subway line. The conclusion and discussion can be found in Chapter 6 and Chapter 7.

2 Current maximum discharge before flooding of the U4

2.1 Background

The Wien River finds its origin in the Wienerwald, west of Vienna, and enters the city after approximately 20 km. The river discharges into the Donaukanal. The historical hydrology of the Wien River cannot be reconstructed with certainty. However, before the construction of intercepting sewers along the river in the 1830s and its regulation and channelization at the end of the 19th century, the estimated mean annual discharge was approximately 2 m^3/s (Pollack et al., 2016).
Since the flood retention basins that were made in the early 1800's, the 10-year return flood was estimated at 140 m3/s, and the 100-year return flood at 200 m3/s. Due to the high potential losses in the city of Vienna, the Wien River is designed to withstand a 1000-year discharge return period (Faber & Nachtnebel, 2002).

2.2 Determination of flooding threshold

2.2.1 Literature Study

Compton et al. (2009, p. 54) state: "A failure that results in the release of water to the U4 occurs when the discharge into the Wien River exceeds the given threshold, resulting either in overtopping of the floodwall or collapse of the floodwall due to either foundation scouring or hydrostatic pressure." While failure due to overtopping is a function of the flow rate in the channel, uncertainties in the water flow rate are expected to be minimal since the Wien River is a channelized river with well characterized geometry. More uncertainty is expected in the erosive failure and wall collapse which are a function of the shear at the channel bed and the shear strength of the invert.
According to the report, the failure leading to overflowing of the U4 is expected to occur at a discharge of 530 m3/s. Given the uncertainties in the floodwall's resistance parameters, this critical discharge is modeled as a normal distribution with mean value of 530 m3/s and a standard deviation of 10 m3/s. This means that at a discharge of around 510 m3/s failure could occur with a probability of 5 percent, and at a discharge of around 550 m3/s with a probability of 95 percent. (Compton et al., 2009)

The study of Faber (2006) also analyzed flood risk in an Austrian context, and specifically for the Wien River. He estimated peak flow frequencies using the rainfall-runoff model IHW for the rural catchment and ITWH for the urban areas, and he used Monte Carlo simulations to account for uncertainties. A total of 7000 simulations were performed within the critical range of 400 to 600 m3/s where failures were most likely to occur. Figure 1 shows that the flood walls can handle discharges up to 500 m3/s, while overtopping of the floodwall is almost certain at a discharge of 560 m3/s. The mean value of the discharge capacity before overtopping amounts to 534 m3/s, with a standard deviation of 14 m3/s. The mean value of discharge for structural floodwall failure is 541 m3/s with a standard deviation of 16 m3/s (Faber, 2006).
Faber also analyzed the probabilities of the different failure events, overtopping and structural damage of the flood wall, individually and in combination. The probability of structural flood wall failure without overtopping was not observed in any simulation. The overall system reliability is above 99 percent, which indicates that failure of the flood wall is extremely rare with the used past peak flows. He further analyzed the return periods of the failure events. The installation of the controlled retention basins in 1998 increased the return period of failure from approximately 550 years to 1100 years. This return period exceeds the 1000-year discharge return period the Wien River is designed for (Faber & Nachtnebel, 2002). This deviation is due to limitations of the return period-based design, which does not fully account for uncertainties in flood frequency and

magnitude.

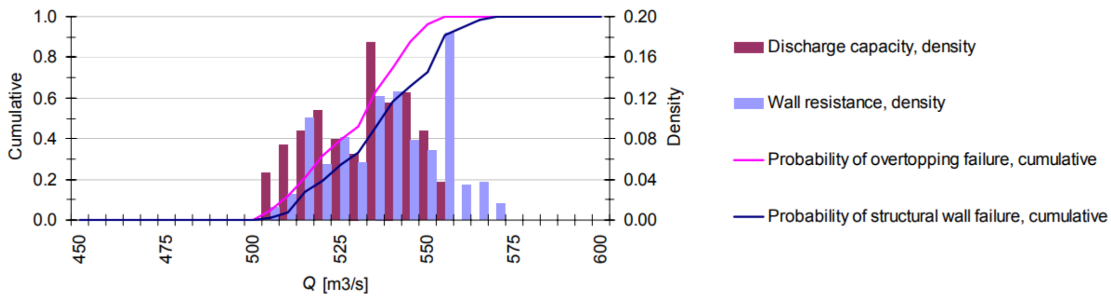

Figure 1: "Distribution of the resistance of the hydraulic system in terms of the bankfull discharge and the flow related to structural floodwall failure"(Faber, 2006)

2.2.2 Conclusion

It can be concluded that the critical event for flooding of the U4 subway line is overtopping rather than structure failure of the flood wall. According to Faber (2006), the mean failure discharge at which overtopping happens is 534 m3/s, with a 5 percent probability at 511 m3/s, and a 95% probability at 557 m3/s. These values align with the threshold values determined by Compton et al. (2009), who estimated a mean failure discharge of 530 m3/s, with 5 and 95 percent probabilities of failure at discharges of approximately 510 and 550 m3/s. The threshold values are normally distributed, so looking at 1 critical threshold value would be a simplification. The probability of exceeding a threshold is heavily dependent on where that threshold is situated in the normal distribution. For this reason the return periods of all discharges in the normal distribution are calculated. This will give an indication of the return period of a certain discharge, and the probability that this specific discharge will lead to flooding of the U4 subway line.

3 Current frequency of threshold exceedance

In this chapter the current frequency of exceeding the threshold determined in Chapter 2 will be analysed. This is done by looking at the available observation data of the catchment area of the Wien River. This observation data is available through eWaterCycle. As determined in Chapter 2, the Wien River is designed for a 1000-year discharge return period. The observation data is unlikely to cover a period of 1000 years, so we will need to extrapolate it to estimate the discharge corresponding to a 1000-year return period and determine the return period of the previously established threshold.

3.1 Observations

First of all, the available observation data will be investigated. This data is available through the Caravan dataset in eWaterCycle. This dataset contains data on precipitation, temperature, potential evapotranspiration and discharge for all the catchment areas available in the Caravan dataset. The Caravan dataset contains a Camel dataset for the catchment area of the Wien River. The discharge observations can be seen in the graph below.

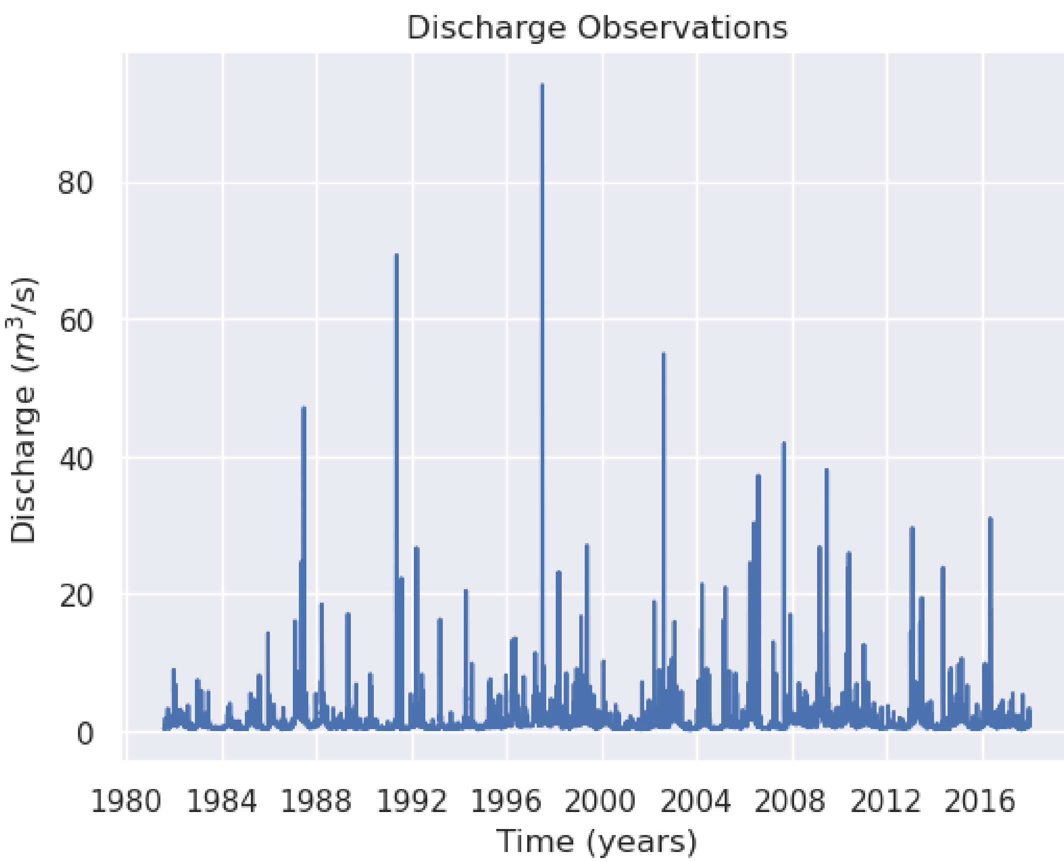

Figure 2: Discharge Observations

The observation data is available from 01-08-1981 to 01-01-2018, which covers a period of 36 years and 5 months. The highest peak present in this dataset has a discharge of 94.05 m3/s. Since there is no peak present in this dataset with a discharge value of the threshold value for flooding, the observation data will need to be extrapolated.

3.2 Extrapolation

The observation data is plotted in the graph below in the form of a scatter plot, with on the y-axis the discharge and on the x-axis the corresponding return period. The blue line is fitted through the observation data, and is extrapolated to be able to find out the return period for the threshold value.

The fit 1 to fit 4 lines represent fitted lines where one or more of the observed data points are missing.

- fit 1 misses the highest peak
- fit 2 misses the second highest peak
- fit 3 misses the two highest peaks
- fit 4 mises the five highest peaks

These lines are plotted as well to give an indication of the influence of certain peak discharges on the extrapolation. This will be useful later in the research, when the significance of the difference in future return periods with different climate change scenarios compared to the current return periods needs to be assessed.

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For a mean threshold value of 530 m3/s, the return period is 640.908 years for
↪fit all data

For a mean threshold value of 534 m3/s, the return period is 649.858 years for
↪fit all data

For a discharge of 530 m3/s, the return period is 922.727 years for fit 1

For a discharge of 530 m3/s, the return period is 729.261 years for fit 2

For a discharge of 530 m3/s, the return period is 1117.978 years for fit 3

For a discharge of 530 m3/s, the return period is 2098.402 years for fit 4
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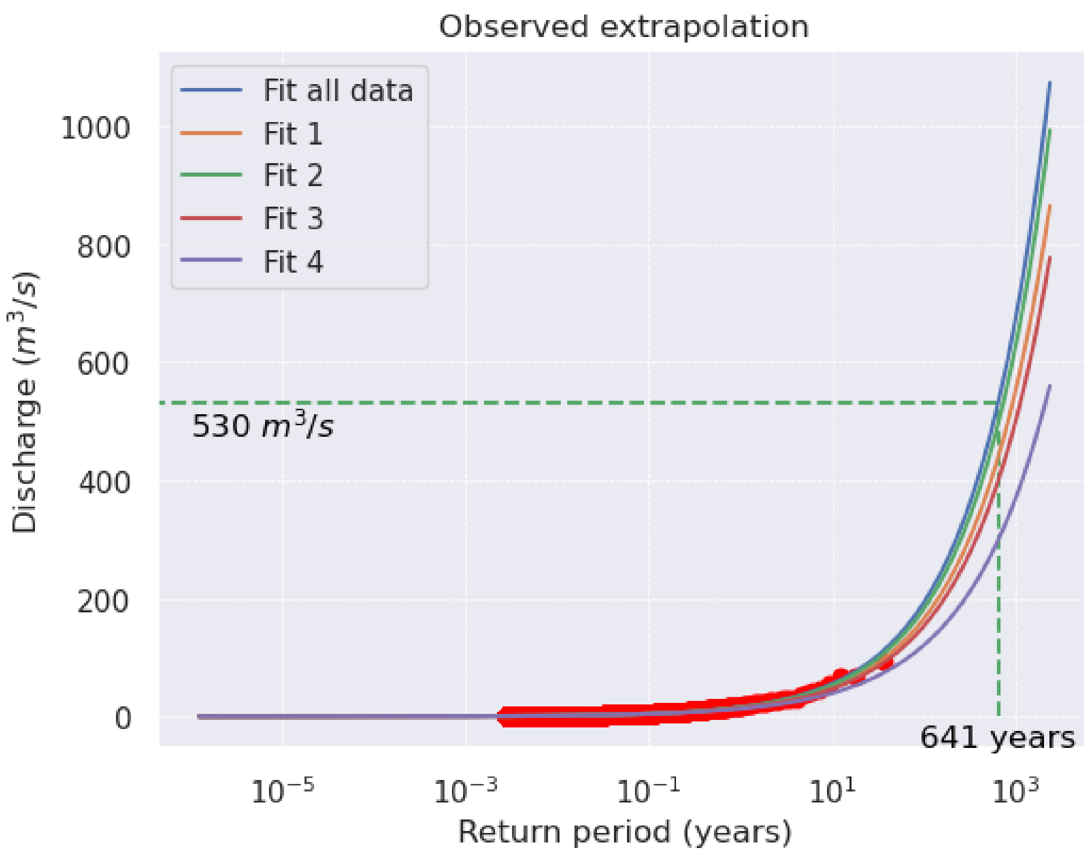

Figure 3: Observation Extrapolation

In the graph above it can be seen that the presence of certain peak discharges in the data have a big influence on the extrapolation. Looking at a discharge of 530 m3/s, the use of all data results in a return period of 641 years. Removing the highest discharge value results in a return period of 923 years, and removing the five hightest peaks results in a return period of 2100 years for a discharge of 530 m3/s. This is important to consider when comparing the model output to the observations.

In the graph below both the normal distribution of the exceedance threshold values and the extrapolated return periods are plotted. A discharge value more to the right of the normal distribution, has a higher return period, but also has a higher probability of actually causing flooding of the U4 subway line.

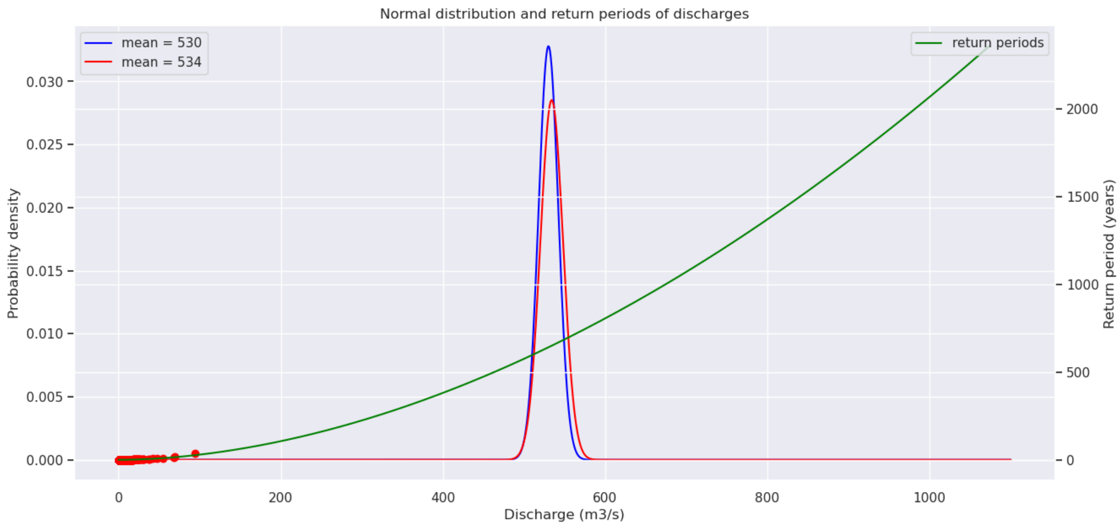

Figure 4: Normal distribution and return periods of discharges

3.3 Conclusion

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4 Calibration of the HBV model

In this chapter the HBV model is calibrated using the observation data. A set of parameters is used by the HBV model to model the discharge. These parameters are calibrated to make the model work for the catchment area of the Wien River.

4.1 Model Selection

To be able to model the expected future discharge, the Hydrologiska Byråns Vattenbalansavdelning (HBV) model is chosen. The developer of the model, Sten Bergström (1992), says the HBV model can best be classified as a semi-distributed conceptual model. The model represents a catchment area by using interconnected storage reservoirs to simulate the movement of water. By adjusting nine parameters, the HBV model can be calibrated to different catchment areas.

The nine parameters that have to be calibrated are Imax, Ce, Sumax, Beta, Pmax, Tlag, Kf, Ks and FM. The parameters represent the following: - Imax: - Ce: - Sumax: - Beta: - Pmax: Maximum percolation rate - Tlag: Time lag - Kf: Fast run-off parameter - Ks: Slow run-off parameter - FM: Field moisture capacity (Wawrzyniak et al., 2017)

A visual representation of the HBV model can be seen in the figure below.

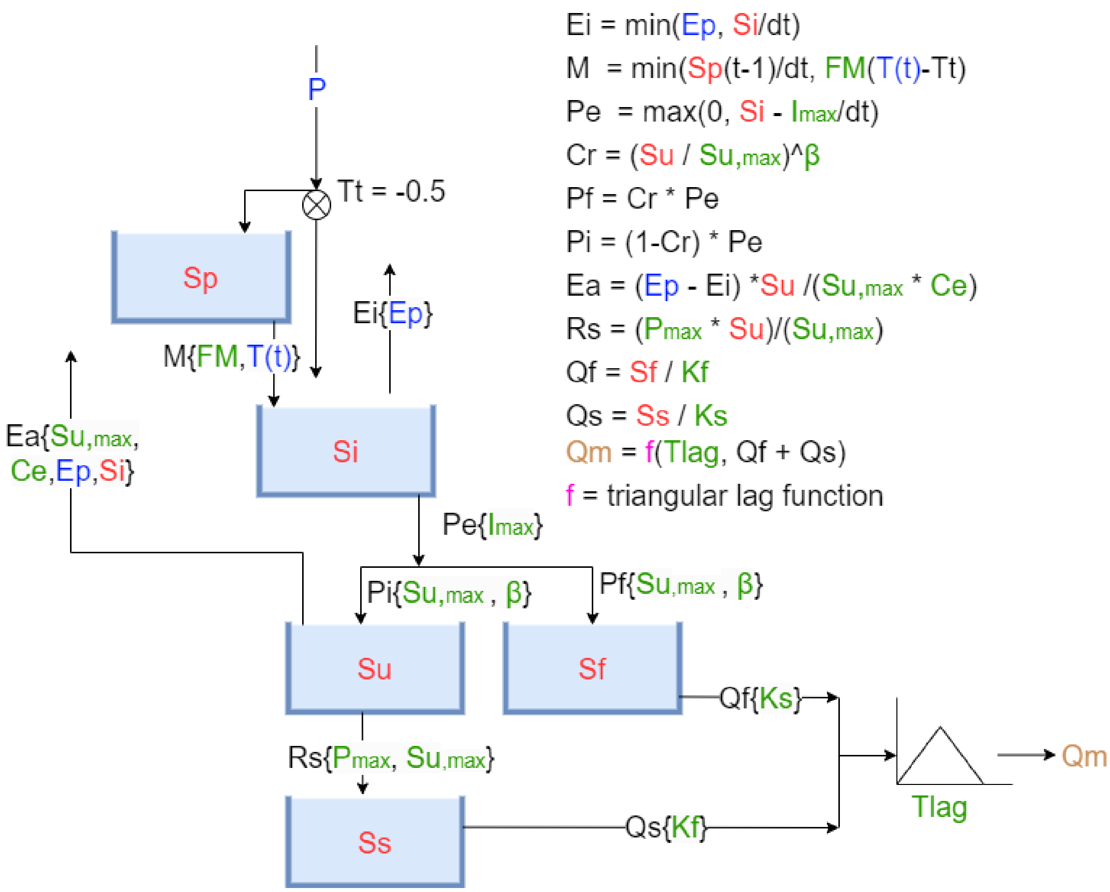

Figure 5: Layout HBV Model (Hrachowitz, M)

4.2 Calibration

The model's performance with a certain parameter combination is assesed by evaluating how well it represents the distribution of discharges, since for my research the exact timing of certain discharges and peaks is not relevant. To measure the difference between the observed and modelled discharges, the root mean squared error (RMSE) is used. The Nelder-Mead optimization is then applied to find the best set of parameters that results in the lowest RMSE. The model is trained on the first 75 percent of the observation data, and is then tested on the last 25 percent of the data. The test shows how well the model performs on data it has never seen before.

4.2.1 Root Mean Squared Error

The Root Mean Squared Error (RMSE) is used to calculate the average overall difference between the observed and modelled discharge. First, the difference between the observed and modelled discharge is calculated for each day, called the error. The RMSE squares this error to give more weight to large differences, such as when observed peaks are not modelled well. This method causes peaks to contribute more heavily to the RMSE. After this, the mean of all squared values is taken, before the square root is applied to get the RMSE.

4.2.2 Nelder Mead Optimization

The optimal parameter combination that results in the lowest RMSE is calculated using Nelder-Mead Optimization.

The parameter combination that resulted in the best perfoming modelled discharge is as follows:
Imax = 0.00
Ce = 1.324
Sumax = 100.048
Beta = 3.894
Pmax = 0.666
Tlag = 0.043
Kf = 1.005
Ks = 1.94
FM = 0.459

The observed and modelled discharges and their distributions for the calibration period can be seen below in figures 6 and 7.

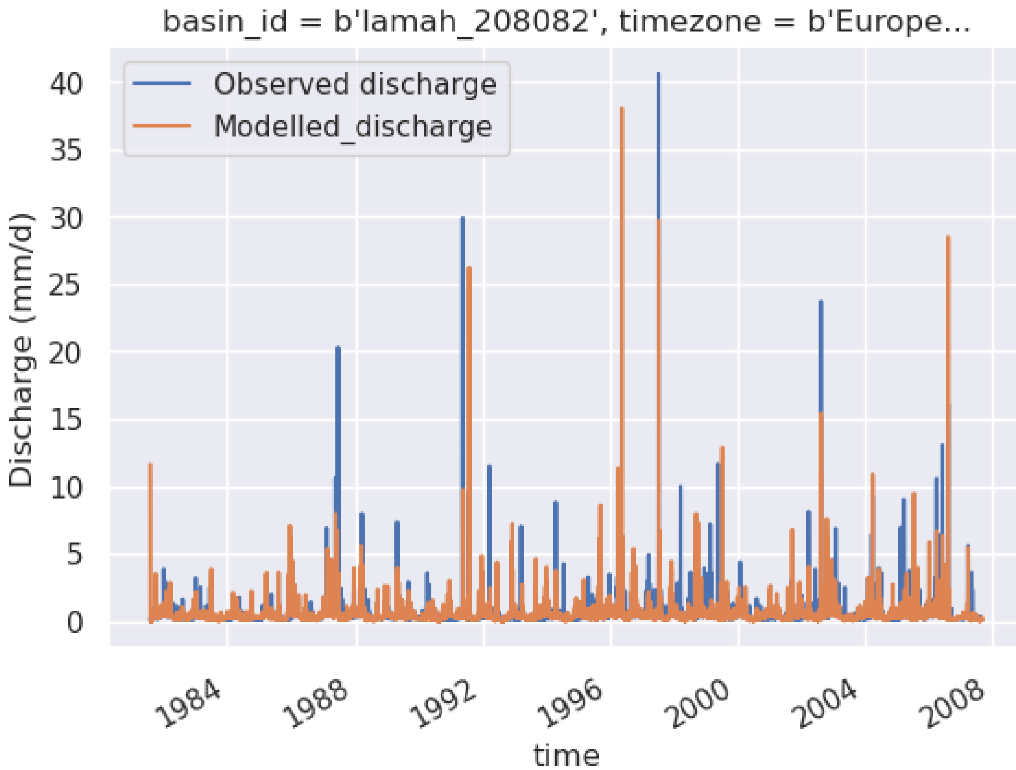

Figure 6: Modelled and observed discharge calibration period

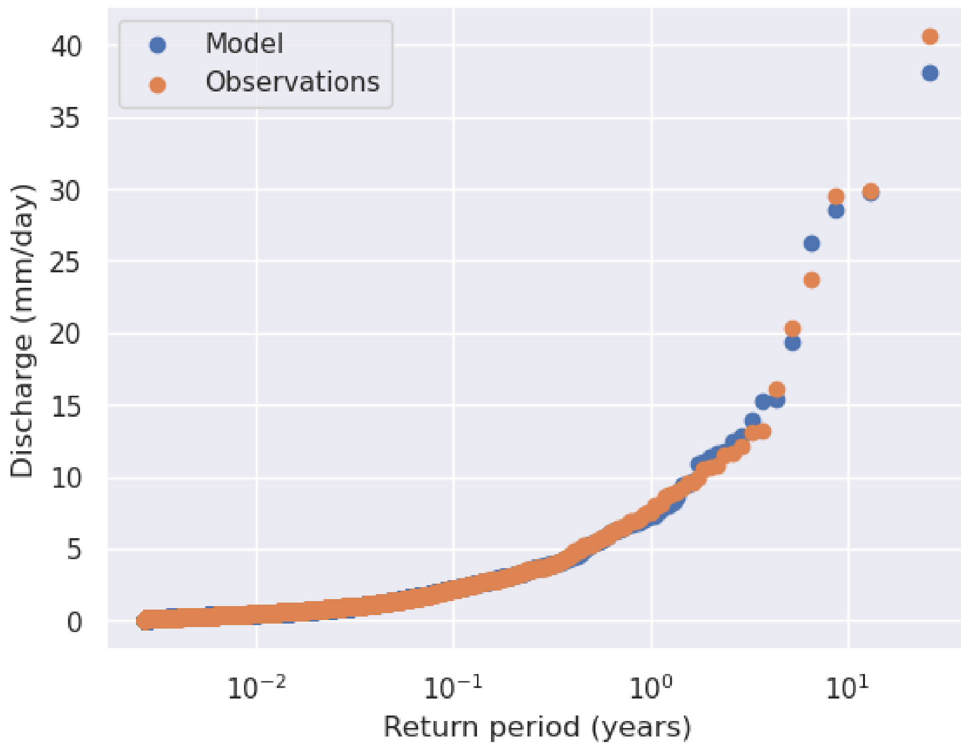

Figure 7: Modelled and observed discharge distribution calibration period

To test the ability of the model to predict discharges for periods of which it has never seen data before, the modelled discharge for the validation period is compared to the observed discharge. This can be seen in figure 8. In figure 9 the distributions of the modelled and observed discharges in the validation period can be seen.

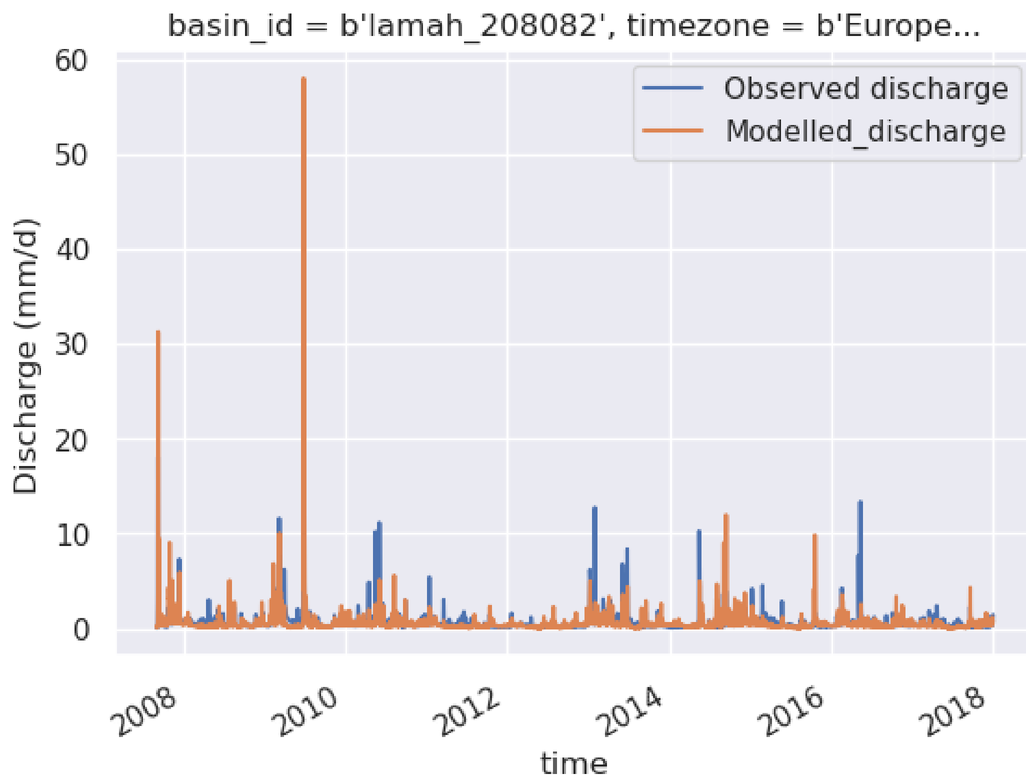

Figure 8: Modelled and observed discharge validation period

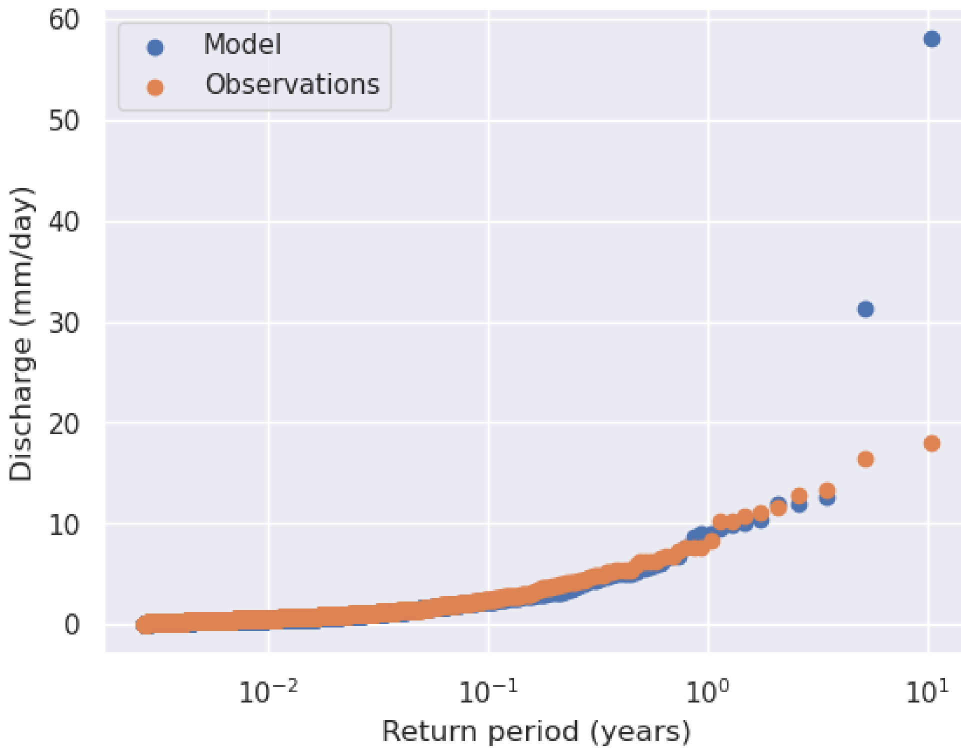

Figure 9: Modelled and observed discharge distribution validation period

The RMSE for both the calibration and validation period can be calculated and compared. The RMSE of the calibarion period is 0.0632, and is 0.7020 for the validation period. The RMSE of the validation period is around 11 times larger than the one for the calibration period. The cause of the RMSE being larger for the validation period is visible in figure 9 above. The model predicts more larger peaks than observed. This is caused by the availble observation data. The last period of the observation data contains no peaks, while the rest of the data does contain peaks. This causes the model to overestimate the actual amount of peaks present in the validation period. Later in this chapter the return period of the threshold value is calculated by extrapolation of the modelled data. If the model works well enough with this parameter combination for the catchment area of the Wien River will be assessed in this part.

To be able to compare the model output to the observation data, the model output is converted from mm/day to m3/s as well. This is plotted below.

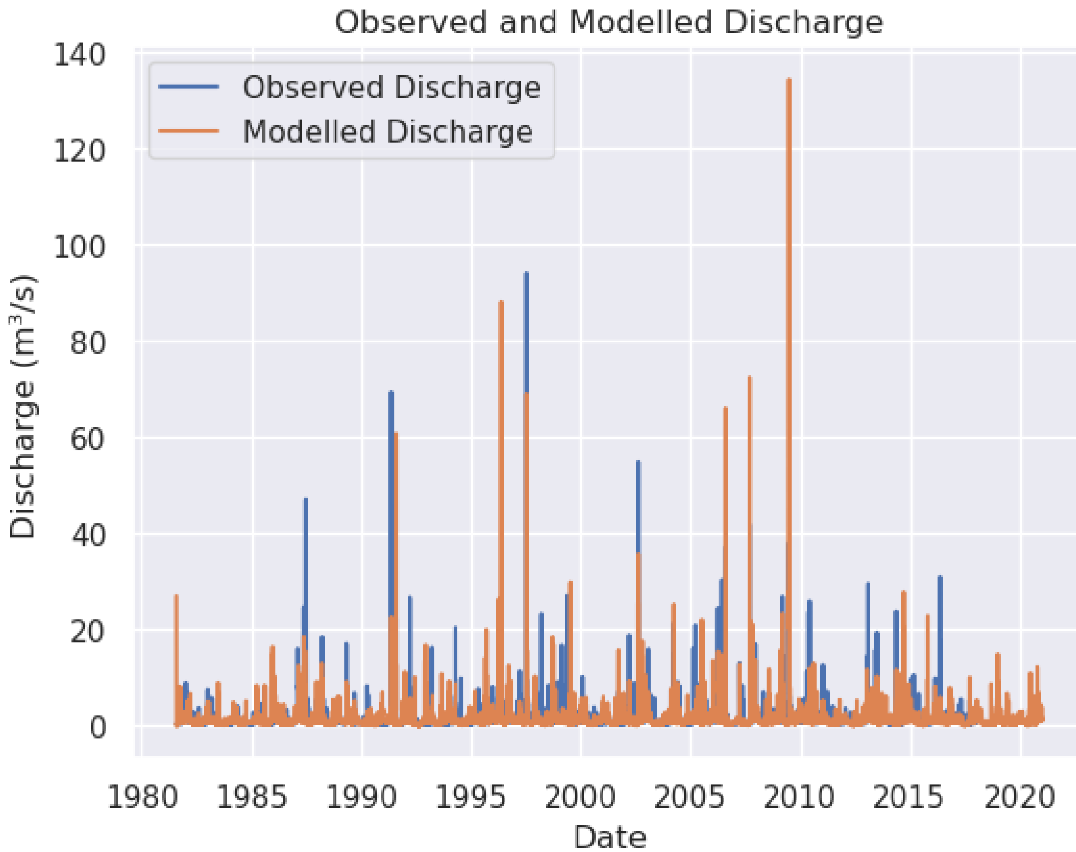

Figure 10: Modelled and observed discharge

To check whether or not the modelled hydroghaph is realistic, the plot in figure 11 zooms in on a period of two years. It can be seen that the model follows the discharge patterns quite well, which means the modelled discharge can be seen as realistic.

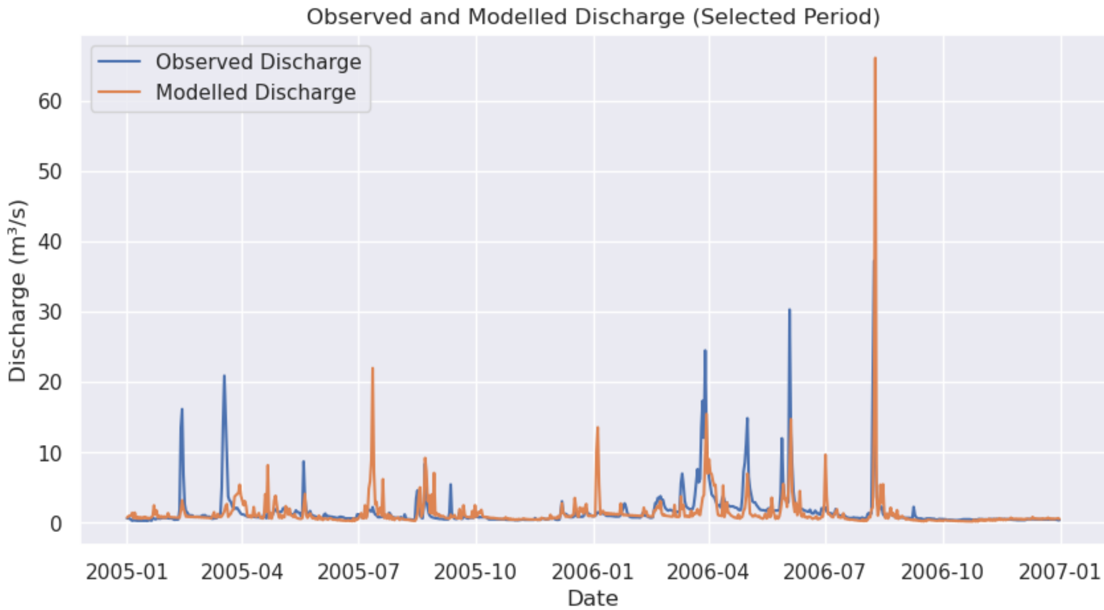

Figure 11: Modelled and observed discharge (2-year period)

Below, in figure 12, the distribution of the modelled discharge is plotted. The blue line is fitted through the modelled data, and is extrapolated to be able to find out the return period for the threshold value. It can be seen that a discharge of 530 m3/s has a return period of 398 years. In Chapter 3, the observed data resulted in a return period of 641 years for a discharge of 530 m3/s. These two extrapolated return periods are not exactly the same. In Chapter 3, the influence of peaks in the data was considered as well. Removing the highest peaks resulted in a return period of 923 years. Removing peaks from the data increases the return period. Removing the lowest discharges decreases the return period. The model overestimates the amount of peaks in the data, resulting in a smaller return period. Overestimating peaks is safer than underestimating peaks, because it prevents underdesigning of flood protection infrastructure and improves the preparedness for floodings. Since it can not be expected from the model to perfectly predict the discarges, a return period of 398 years for a discharge of 530 m3/s is considered close enough to the return period of 641 years for the observed data.

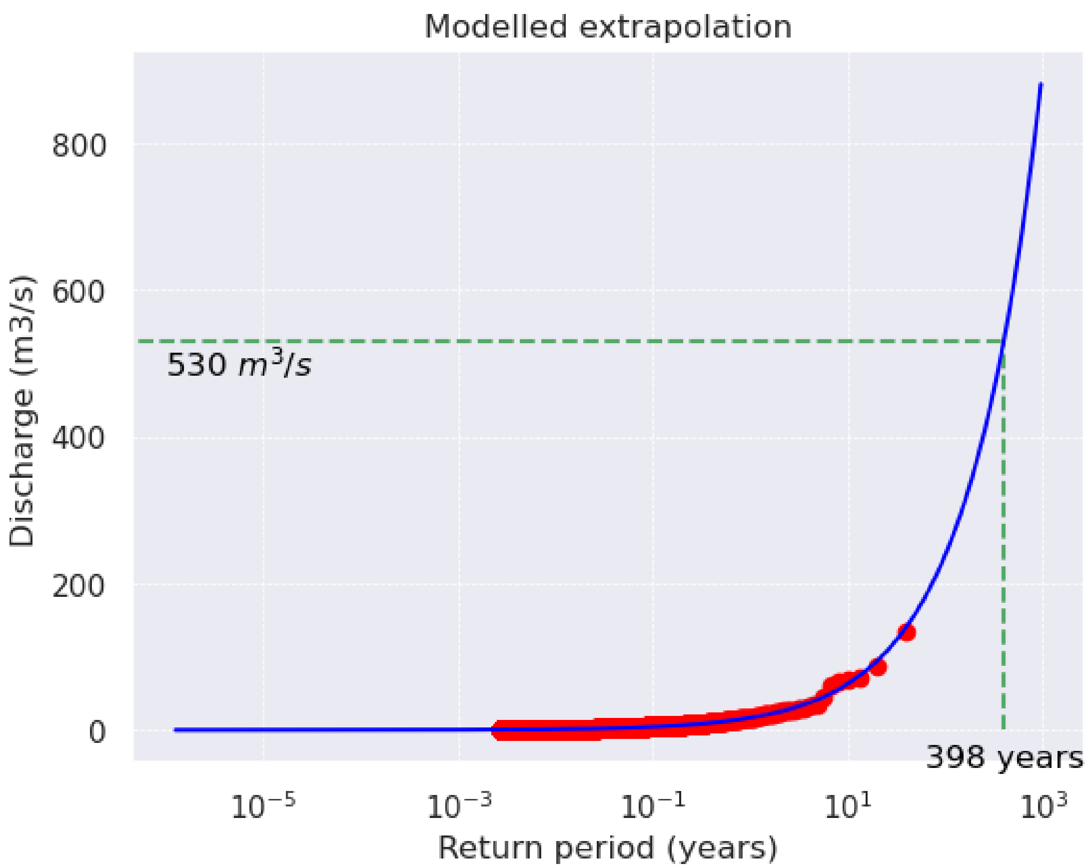

Figure 12: Modelled discharge extrapolation

5 Future frequency of threshold exceedance under different climate change scenarios

In this chapter the future frequency of threshold exceendance is determined. This is done using forcings based on different climate change scenarios, the Shared Socioeconomic Pathways (SSPs). Shared Socioeconomic Pathways are a set of narratives that outline potential future scenarios for human society, focussing on the use of fossil fuels and the social and economic factors that influence the consumption of fossil fuel (ClimateData.ca, 2025). The five main SSPs (Meinshausen et al., 2020) are being considered : - SSP1-1.9: scenario of the ‘sustainability’ socio-economic family, reflects most closely a 1.5 °C target under the Paris agreement - SSP1-2.6: ‘sustainability’ scenario as well, with a radiative forcing level of 2.6 W m−2 in 2100 - SSP2-4.5: scenario of the ‘middle of the road’ socio-economic family, which implies continuing with current development patterns, with a 4.5 W m−2 radiative forcing level by 2100 - SSP3-7.0: medium-high reference scenario in the ‘regional rivalry’ socio-economic family - SSP5-8.5: high reference scenario in the ‘fossil-fueled development’ socio-economic family
(Meinshausen et al., 2020; ClimateData.ca, 2025)

5.1 Historical Comparison

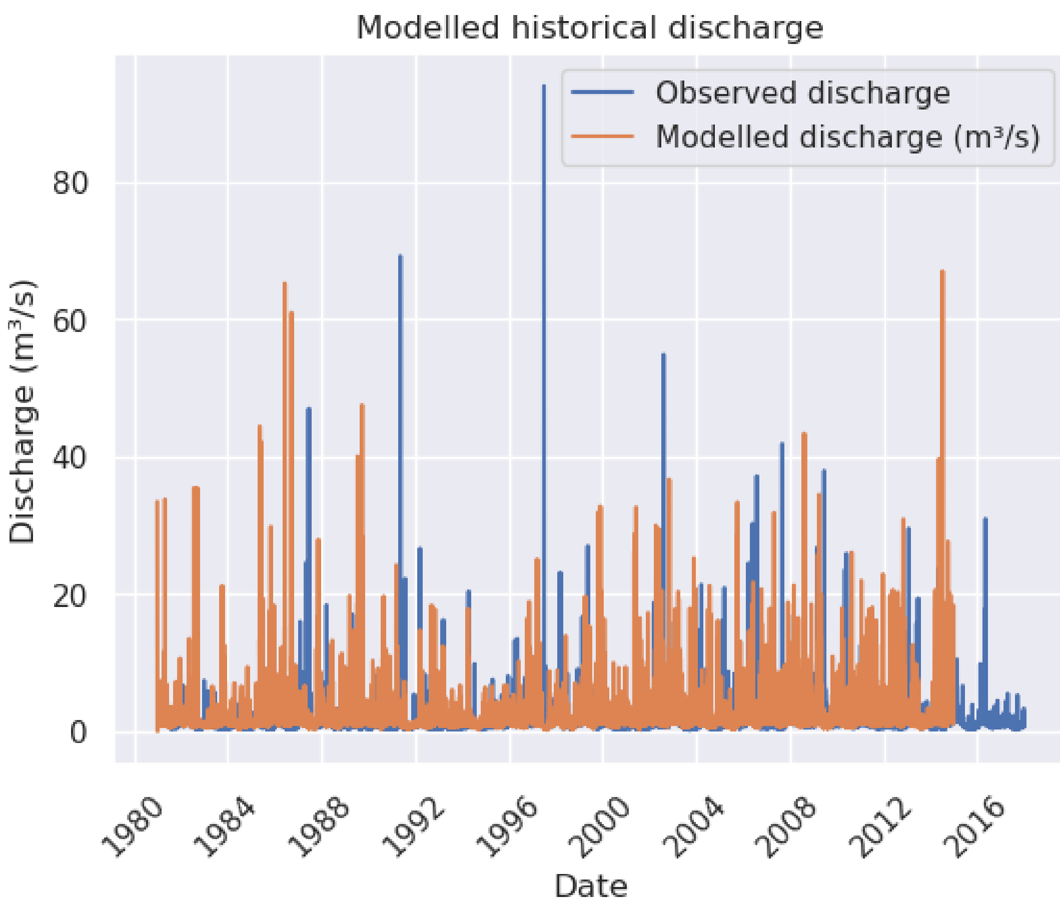

Figure 13: Historical discharge using CMIP

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For a mean threshold value of 530 m3/s, the return period is 819.058 years for␣
↪fit all data
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For a mean threshold value of 534 m3/s, the return period is 832.163 years for␣
↪fit all data
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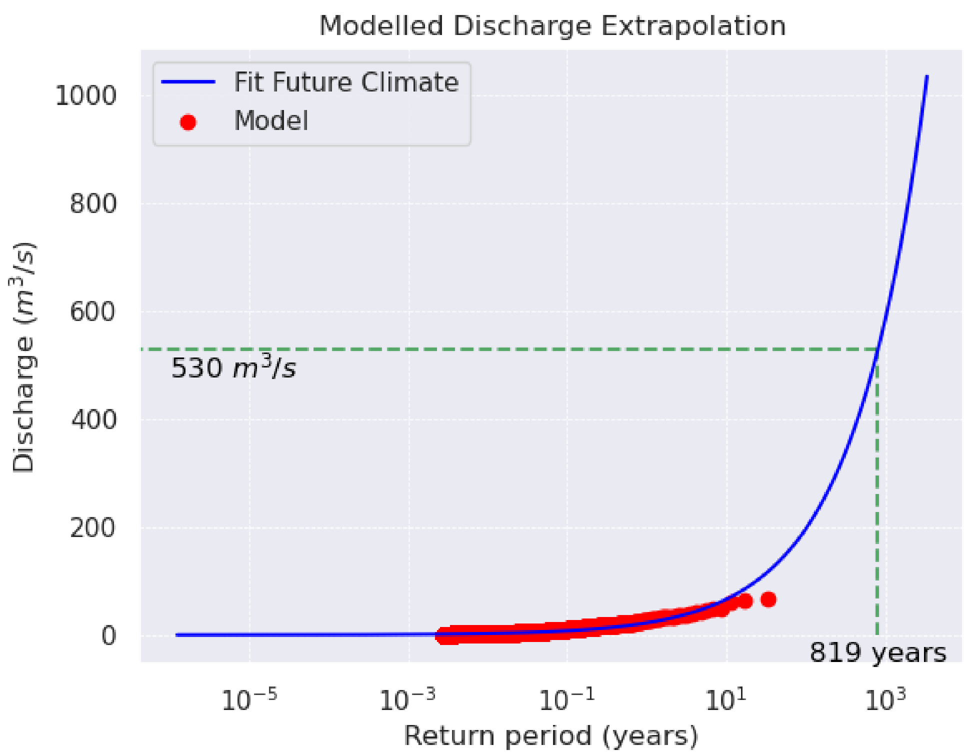

Figure 14: Historical modelled discharge distribution and extrapolation using CMIP

5.2 Future Scenarios

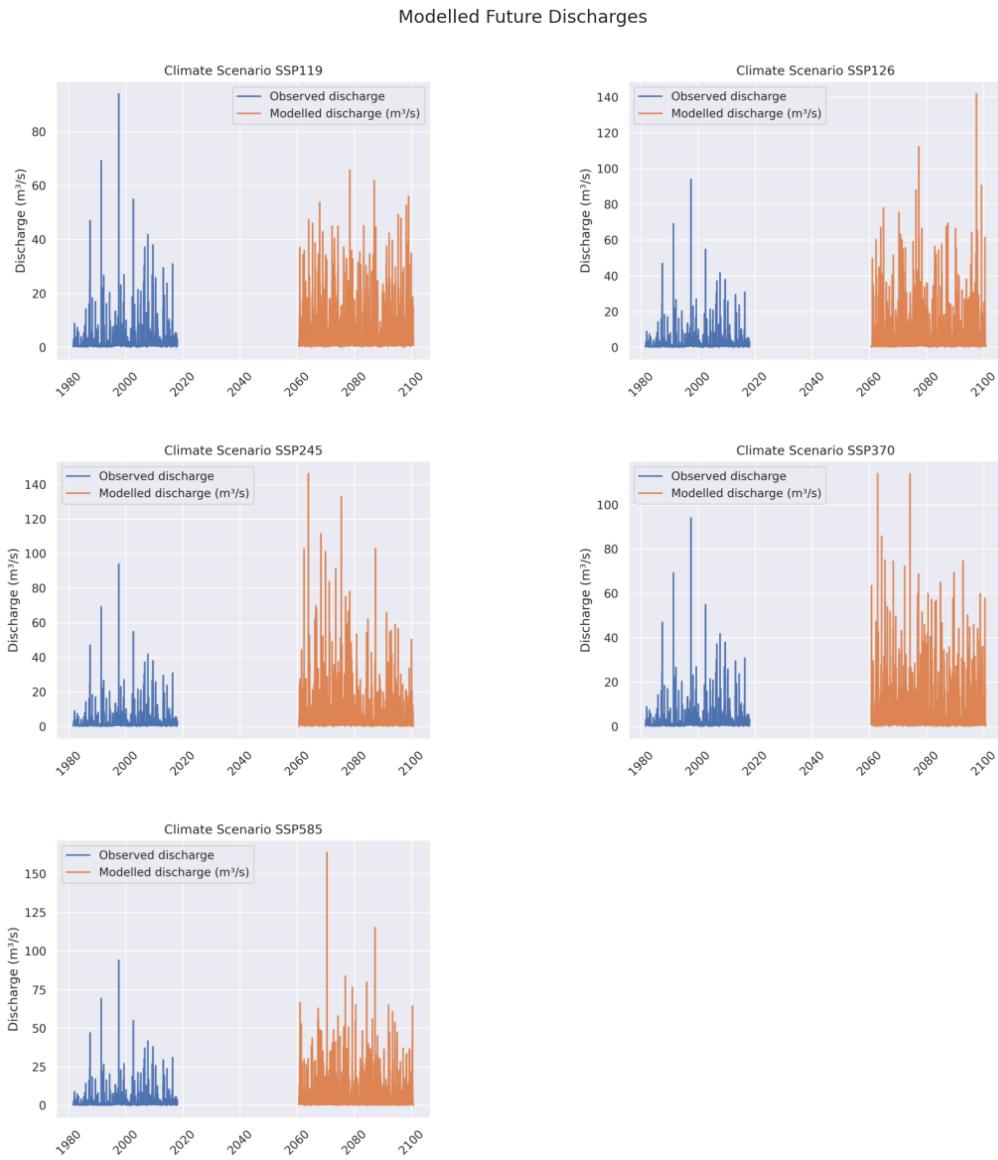

Figure 15: Modelled discharge for different climate change scenarios

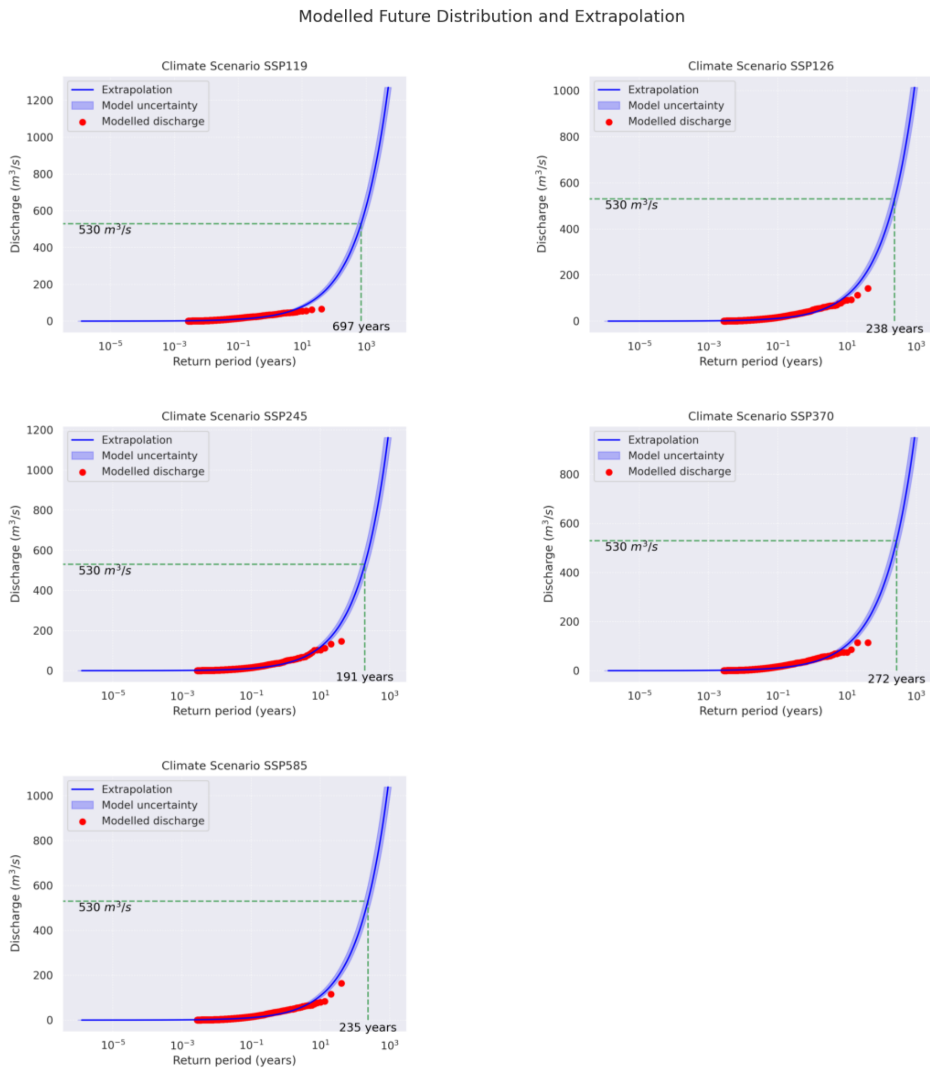

Figure 16: Modelled discharge distribution and extrapolation for different climate change scenarios

6 Discussion

7 Conclusion

8 Recommendation

9 Appendix I