The effect of climate change on the Loire River

A research using eWaterCycle

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TU Delft

Figure: Reuters (2022)

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A research using eWaterCycle

By

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In partial fulfilment of the requirements for the degree of:

Bachelor of Science
in Civil Engineering and Geoscience

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Preface

To complete my bachelor's program in Civil Engineering and Geosciences at Delft University of Technology (TU Delft), I had to write a thesis on a subject of interest. Among all the topics covered in my studies, hydrology stood out as the one I enjoyed the most. Additionally, climate change is a subject I find increasingly important in today's world, which led me to choose the topic: "Impact of Climate Change on a River of Choice."

With Europe experiencing significant changes due to climate change, I knew I wouldn’t have to look far to find a suitable river for my research. After reading about the record-breaking droughts in France, it became clear that the Loire River would be a perfect case study. Its hydrological challenges in the face of climate change make it a compelling subject for analysis.

For further insight into the methods used to analyse drought, the complete repository for this research is available on GitHub via the following link:

https://github.com/eWaterCycle/projects

Contents

Abstract

This study investigates the impact of climate change on drought characteristics in the Loire River basin. Climate change is expected to intensify drought conditions globally, with significant implications for water resources. This research aims to assess how future droughts in the Loire basin will evolve under different climate scenarios, focusing on changes in drought duration and severity.

To achieve this, the hydrological system of the Loire was analysed to identify drought causes and define drought conditions using a critical water flow threshold. For this research, the station Blois-sur-Loire was selected, with a critical water flow set at 66.5 m^3/s. This threshold was applied to detect historical droughts.
An algorithm was developed to calculate both the maximum water shortage and the drought duration, the time required for water flow to return to normal after a drought. This algorithm was used to calibrate the HBV hydrological model on historical data to project future discharge conditions accurately. The model was calibrated based on the distribution of drought duration and deficit.

The calibrated model was applied to three future climate scenarios to assess the impact of climate change under different climatic conditions:

- SSP126: a more optimistic climate future with significant mitigation measures,
- SSP245: a scenario reflecting limited climate action, and
- SSP585: a high-emission, fossil-fuelled driven scenario.

The discharges for these scenarios are generated using CMIP6 MPI-ESM1-2-HR dataset in combination with the calibrated HBV model.

The results, analysed using return periods, reveal a clear trend toward more frequent and severe droughts across all climate scenarios, even under the most optimistic scenario (SSP126). However, the results for SSP126 indicate that climate change measures can mitigate drought impacts compared to the less favourable scenarios (SSP245 and SSP585). The difference in drought duration between SSP245 and SSP585 is minimal, likely due to faster replenishment during winter months. However, drought deficits are projected to become significantly more extreme under higher return periods in SSP585.

Uncertainties remain due to the use of only one CMIP6 ensemble member, which may influence the reliability of future drought projections. Future research is recommended to explore multiple ensemble members and assess the implications for water management strategies in the region.

Acknowledgments

I would like to express my sincere gratitude to my supervisors, Prof. dr. ir. R. Hut, Ir. V. Hoogelander, and Ir. M. Melotto, for their guidance throughout this research. Their insights and constructive feedback have been essential in shaping the methodology and improving the overall quality of this study.

Additionally, I would like to thank the Global Runoff Data Centre (GRDC) for providing valuable discharge data, as well as the eStreams for granting access to their datasets. These resources were crucial for the analysis conducted in this study.

Finally, I would like to give recognition to my family, friends, and my girlfriend, for their support throughout this research period.

The Hague, March 31st 2025,

Ischa Hollemans

1 Introduction

1.1 Background

In the summer of 2022, Europe experienced a prolonged drought, during which a lack of precipitation and a series of extreme heatwaves led to a significant water deficit in multiple river basins (Toreti et al., 2022). This was also the case for the Loire basin, where river discharge reached critically low levels, and some major tributaries dried up completely. Due to climate change, droughts have become more frequent in recent years (Vu, 2023).

1.2 Problem analysis

The Loire is the longest river in France, originating in the Central Massif and flowing over a thousand kilometres before reaching the Atlantic Ocean at Saint-Nazaire. It is widely utilized by the French population, with nearly half of France's grain farming and two-thirds of its livestock farming concentrated along its banks. Additionally, the Loire serves as a crucial water source for electricity generation, supporting both hydroelectric and nuclear power production (WWF France, 2003).
During droughts, these water-dependent sectors are at risk (Debein, et al., 2024). For instance, in 2016, multiple heatwaves caused a severe drought, leading to some districts losing up to 55% of their crops (Nóia Júnior et al., 2023). Furthermore, the four power plants along the riverbanks faced challenges due to the drought, as low river flow and increased water temperatures resulted in suboptimal reactor cooling (ASN, 2022). It is therefore important to research if the situation will worsen in the future.

1.3 Objective

The objective of this research is to quantify the impact of future droughts on the hydrology of the Loire River under different climate change scenarios. This leads to the following research question: How will climate change influence future droughts on the Loire River? This question will be answered using the following sub-questions:

- What are critical low water flows for the Loire basin during droughts?
- How often have droughts occurred in the past?
- How often will droughts occur in the future?

This research focuses on quantifying the frequency and severity of future droughts under different climate scenarios to assess the impact of climate change. The severity of a drought will be defined exclusively by its duration and water shortage. The impact of future droughts on water demand is beyond the scope of this research.

1.4 Approach

To address these research questions, a literature study is first conducted to gain a better understanding of what causes droughts in the Loire basin and how to define them. This involves answering the first research question: "What are the critical low water flows for the Loire basin during droughts?" This critical water flow is then used to identify past droughts and predict future droughts. To generate future droughts, a hydrological model is required.

For this research, eWaterCycle is used. eWaterCycle is a hydrological modelling platform that simplifies the use of various models by allowing users to switch between them, compare them, or even use them together (Hut, 2022).
The model selected for this study will be based on availability in eWaterCycle and prior hydrological research conducted on the Loire basin. Once the appropriate model is chosen, it will be calibrated and validated using historical data to ensure its reliability before applying it to future climate scenarios. An overview of the hydrological model implementation is displayed in *figure 1:*

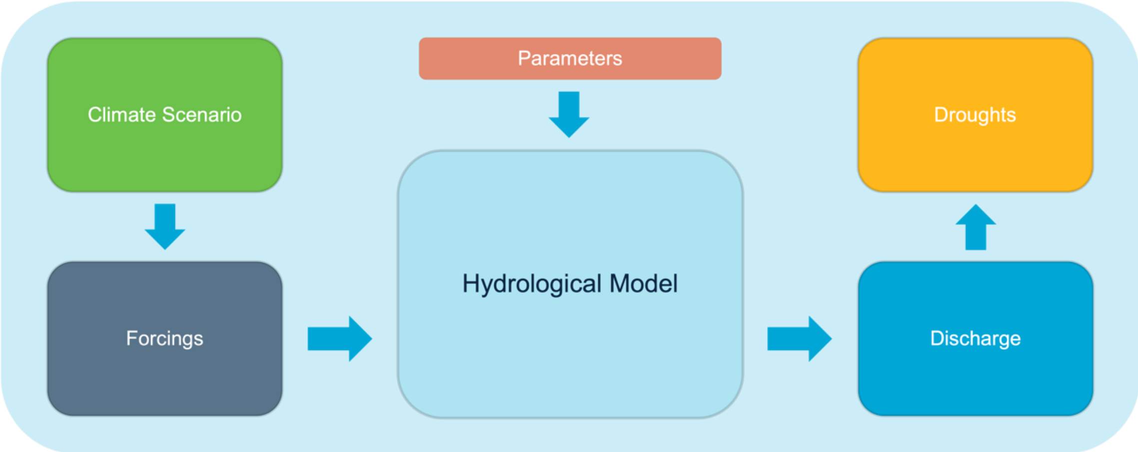

Figure 1: Overview of the application of the hydrological model.

The results from the future scenarios will offer quantitative insights into projected changes in river discharge and drought severity for the Loire basin.

1.5 Reading guide

Chapter 2 presents a literature review examining the hydrological aspects of the basin and defining a critical water flow for droughts. In Chapter 3, a historical analysis is conducted after selecting a suitable hydrological model. Chapter 4 applies this model to predict future water flow under different climate scenarios. The results are analysed in Chapter 5, followed by a discussion of the findings in Chapter 6. Finally, Chapter 7 presents the conclusion of this research.

2 Literature study

2.1 The hydrological system of the Loire

The Loire basin is mainly supplied by precipitation, which means that runoff can vary significantly during periods of heavy rainfall or drought. Runoff is usually high in winter and low in summer. At the mouth of the river, the mean discharge in January is around 1,800 m³/s, while in August, it drops to 250 m³/s (Monteil, et al., 2010). This pattern is also evident in *figure 2*, which uses historical data from the Blois (the choice for Blois is explained in 2.2), a measurement station more upstream, to illustrate the difference in mean monthly flow between January and August. The average monthly flow in January is approximately 560 m³/s, whereas in August, it drops to around 115 m³/s.

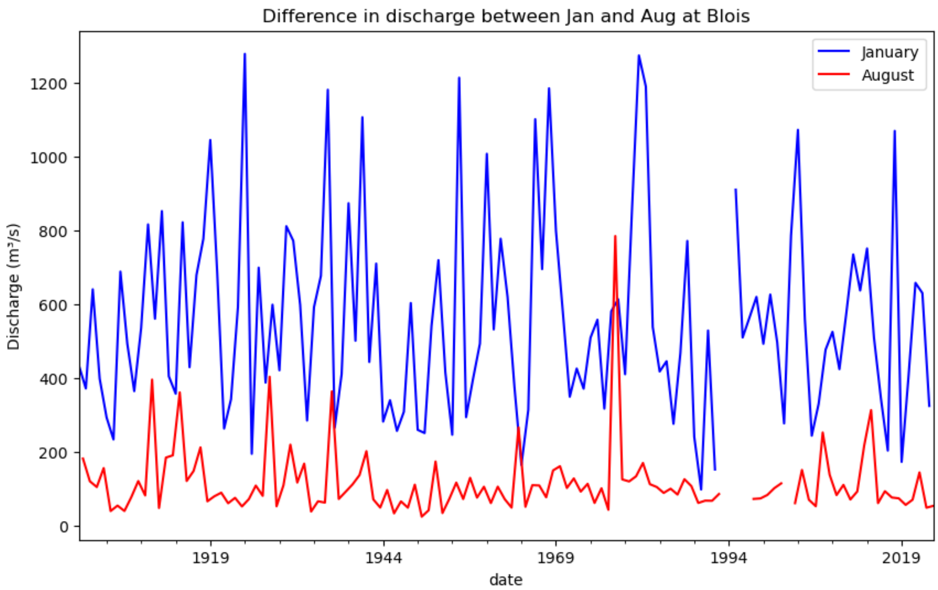

Figure 2: Monthly mean discharge for January and August to show the difference in river flow during low precipitation month (August), and high precipitation month (January).

The contribution of aquifers for the total catchment area is minimal, with a mean discharge of around 6 m³/s in summer and 13 m³/s in winter. The impact of snowmelt is also limited, occurring only between January and May. The Loire basin contains multiple reservoirs that help regulate water levels by mitigating floods and replenishing the river during droughts. The main reservoirs, located in Villerest and Naussac, have a combined capacity of 425 million m³ (Moatar, et al., 2022). During prolonged periods of no rainfall, these reservoirs become depleted and can no longer maintain the river's discharge above a critical threshold.

Therefore, precipitation is the main factor influencing low water discharge.

2.2 Critical water flow for the Loire

To measure periods of drought, it is essential to define a water flow that is associated with drought. To achieve this, a critical water flow needs to be defined for a measurement station of choice. For this case, Blois-sur-Loire is chosen, as this is one with the most historical data.

After the extreme drought in 2022, the official state representative for the Loire department published a report on drought conditions (Préfet d'Indre-et-Loire, 2023). Measurement station Blois-sur-Loire is not mentioned in this report, yet the Gien measurement station is, which is approximately 100 km upstream of Blois. Within this distance there are no major tributaries flowing into the Loire, yet the catchment area is significantly different as visible in *figure 3*. Consequently, the critical discharge from Gien needs to be recalculated for Blois.

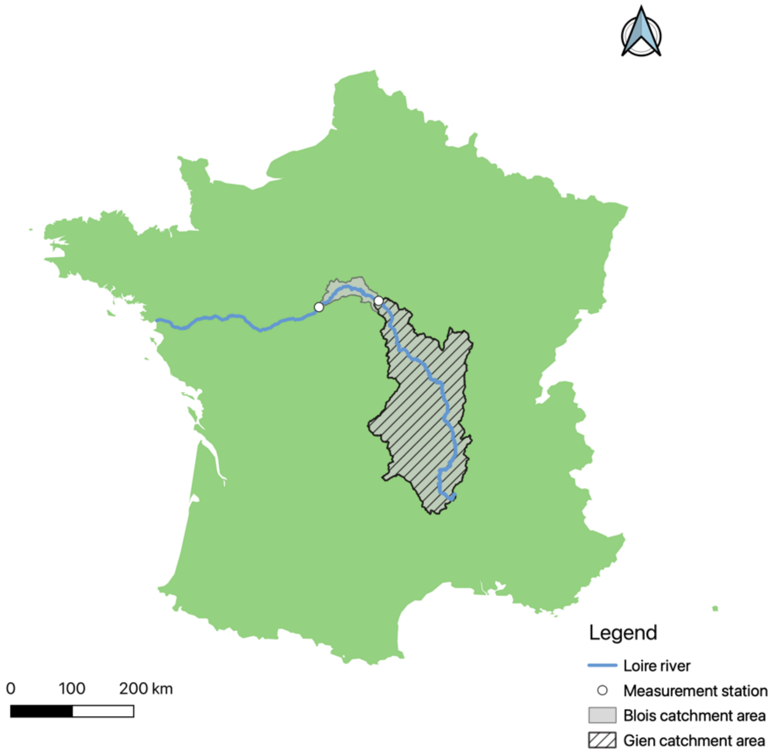

Figure 3: Overview of the measurement stations used in this research and the associated catchment areas.

In the report of the Préfet d'Indre-et-Loire, there is a distinction made between multiple management levels based on low water flow in Gien. The first level is 'vigilance' with a flow of 60 m³/s, where communication and awareness measures are started if the low water trend is expected to sustain. The second level is 'heightened alert' with a flow of 50 m³/s, where the first limitations of water use are implemented. The main restrictions are on personal water use, where unnecessary water demands are partially or fully restricted. Watering sport fields and gardens is prohibited during the day. Filling private swimming pools or fountains becomes fully restricted. The third level is 'reinforced alert' with a flow of 45 m³/s, where most of the partially restricted measures become fully restricted. The final level is 'crisis' with a flow of 43 m³/s, where only water use to guarantee the safety and health of the French population is permitted.

To evaluate if this crisis discharge can function as the critical water flow for this research, it must be a suitable indicator of drought conditions. At another station Montjean-sur-Loire downstream of Blois, about which more literature is available, the crisis discharge is equal to 100 m³/s. This discharge only occurred three times in over fifty years: in 1976 and twice in the last six years, 2019 and 2022. In these three extreme cases the discharge has not gone much below the crisis level of 100 m³/s (Préfet de Maine-et-Loire, 2023). Since the crisis threshold is only rarely exceeded, it represents an extreme rather than a continuous indicator of drought conditions.

This suggests that the crisis level is not a clear indicator for the beginning of a drought period. On the other hand, the second measurement level is where the impact of low water flow starts to affect water availability, so the ‘heightened alert’ level is a better fit for this research. Thus, the critical water flow for Gien is equal to 50 m^3/s.

This critical water flow must be adjusted to accurately represent the corresponding flow at the Blois station. To achieve this, the historical discharge data for both Gien and Blois were analysed. Since only monthly data is available on Global Runoff Data Centre (GRDC) for Gien, the comparison is conducted using monthly records.

To determine the critical water flow for Blois, an algorithm is used. This algorithm identifies the number of instances where the recorded flow at Gien falls below its critical threshold. The same number of occurrences is then applied to the Blois data to establish its corresponding critical flow value. The adjusted critical water flow for Blois is equal to 66,5 m^3/s.

3 Historical droughts

Historical discharge data is essential to eventually predict future droughts. The data is needed to assess whether the hydrological model and the drought analysation method are accurate.
For this purpose, historical discharge from the eStreams database was used, providing observed records for the Blois-sur-Loire catchment (do Nascimento, et al., 2024). The data spans from 1900 to 2023, allowing for an analysis in this period.

3.1 Model selection

To select an appropriate hydrological model, relevant studies on the Loire River were reviewed. Évaluation des Ressources en Eau des bassins Sud-Ouest (EROS) has been applied multiple times as hydrological model (e.g., Seyedhashemi et al., 2022; Garnier et al., 2018). However, EROS is not well-suited for this study because it accounts for groundwater interactions and human interventions, requiring additional data (Thiéry, 2018).
A more suitable option is the Hydrologiska Byråns Vattenbalansavdelning (HBV) model, which is widely used due to its simple structure, relatively low data requirements, and reliable performance (Seibert & Bergström, 2022). Given these advantages and the availability on the eWaterCycle platform, HBV was selected for this study. The output of the model is examined to assess if the model is a good fit.

3.2 Drought analyser

To analyse past droughts, an algorithm is developed (see Appendix A). This algorithm detects droughts and assesses them on duration and severity. For this research, the severity of a drought is defined by the maximum water shortage (deficit) during a drought. The algorithm achieves this by detecting the date where the discharge falls below the critical water flow of 66.5 m³/s. This is the start of a drought, and thus the beginning of a deficit. For each day onward, the algorithm calculates the difference between current discharge and the critical flow:

$$D(t) = (Q(t) - Q_{crit}) \tag{1}$$

If the value is negative, it stands for deficit. If the value is positive, it means that the hydrological system gets replenished. The severity of the deficit is quantified by taking the maximum cumulative water deficit which uses the following formula:

$$D_{cum}(t) = \sum_{i=0}^{t} D(i) \tag{2}$$

By using this for every timestep, the following list is created *equation 3*. The maximum cumulative deficit is eventually calculated using *equation 4.*

$$D_{cum,list} = [D_{cum}(1), D_{cum}(2), \dots, D_{cum}(n)] \tag{3}$$

$$D_{max} = \max\left(\text{abs}\left(\left(D_{cum,list}(t)\right)\right) \quad t \in [1, n]\right. \tag{4}$$

The drought period is defined by the amount of time it takes for the system to replenish the amount of lost water. In *figure 3*, a visualisation of the length of a drought $T_{drought}$, and D_{max} is displayed:

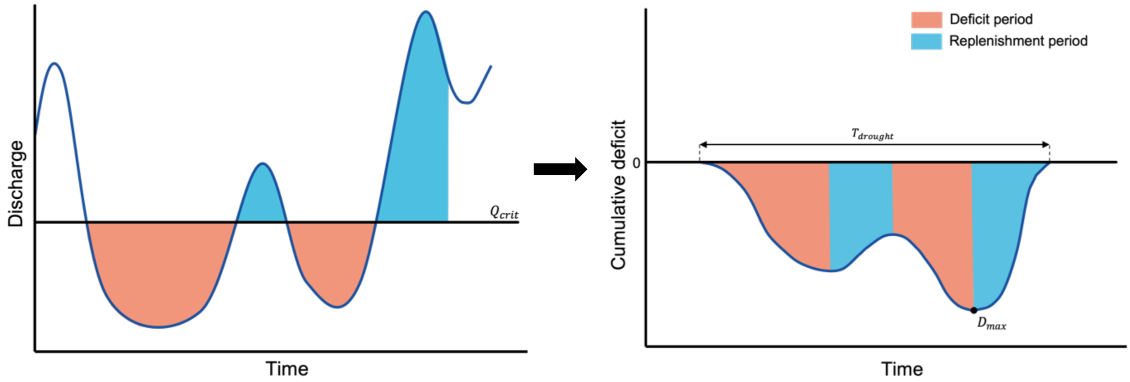

Figure 4: Visualisation of 'Drought Analyser' algorithm. This figure shows how the algorithm detects the beginning of a drought using the Q_{crit}, and how the deficit and replenishment periods are defined to calculate the D_{max}.

3.3 Past droughts

The validation of the drought analyser is done by using known drought years and checking whether the algorithm detects them properly. As mentioned earlier, the most extreme droughts that occurred in the past 50 years are 1976, 2019 and 2022 (Préfet de Maine-et-Loire, 2023). Yet, these droughts were detected at Montjean, which is 200 km downstream of Blois. The algorithm is used on this period, but slight differences are expected due to inflow of tributaries between Montjean and Blois. The results are shown in *figure 5.*

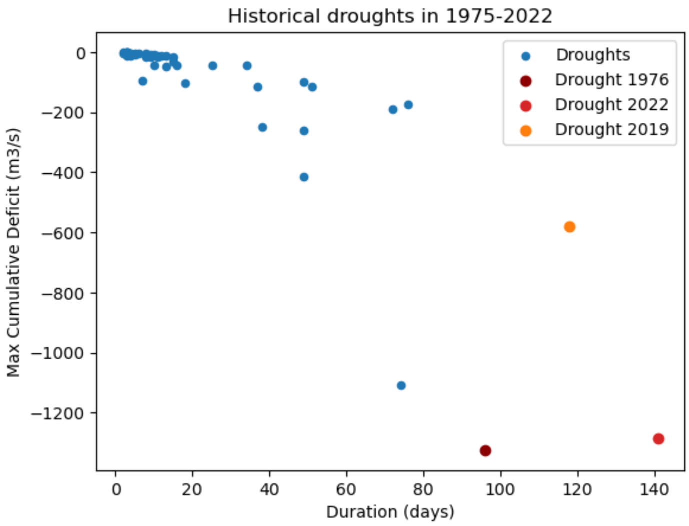

Figure 5: Droughts in the period of 1975-2022

After rearranging the results, based on severity, the algorithm gives the following output for the five worst droughts:

Table 1: Most extreme droughts in 1975-2022 detected by algorithm based on deficit to validate the algorithm.

Drought start date	Duration (days)	Max Cumulative Deficit (m3/s)
1976-06-22	96	1324.1
2022-07-18	141	1286.5
2006-07-15	74	1108.4
2019-07-03	118	577.8
2011-09-22	49	414.6

The algorithm has detected the most extreme droughts successfully, yet based on deficit, the drought of 2006 is worse than 2019. Based on duration, 2019 is more extreme. So, in conclusion the algorithm works as expected.

3.4 Model calibration

To predict and analyse future droughts, the HBV model is used. This model requires the following input: precipitation, surface air temperature, shortwave radiation, and potential evapotranspiration. Precipitation, surface air temperature, and shortwave radiation are generated from the ERA5 dataset. Potential evapotranspiration is calculated using the Makkink equation.
The available ERA5 dataset in eWaterCycle spans from 1990 to 2019, so this period is used to calibrate and validate the HBV model. Due to missing discharge data between 1992–1997 and incomplete records between 2000–2002, the total usable dataset covers 26 years. By using a sample split of 80%/20%, 1990 to 2014 is used for calibration and 2015 to 2019 is used for validation.

The model consists of five stores and nine parameters that define the interactions between these stores. To ensure an optimal model representation, these parameters are calibrated on the historical data from the Blois station. Since high discharge peaks are less relevant for this study, the model is calibrated for low-flow conditions. For this purpose, the model is calibrated on drought durations and water deficit. Initially this was done by using the relation between duration and deficit by using a fitted line, yet this gave inferior results to the current calibration method: distribution of drought duration and water deficit. In this method the distribution of the modelled drought is compared to the observed drought for drought duration and water deficit. By using ‘Earth Mover’s Distance’ (EMD), which calculates the difference between the distributions, it is possible to give a quantitative representation for the parameters. In this case, the lower the output of EMD, the better the parameters fit for this catchment. During calibration, 2000 sets of parameters are generated using ‘Latin Hypercube Sampler’ (LHS), which ensures a well-distributed parameter set.

After running the calibration, the optimal modelled discharge is then validated. The results of modelled discharge and the observed discharge in the validation period is displayed in *figure 6*.

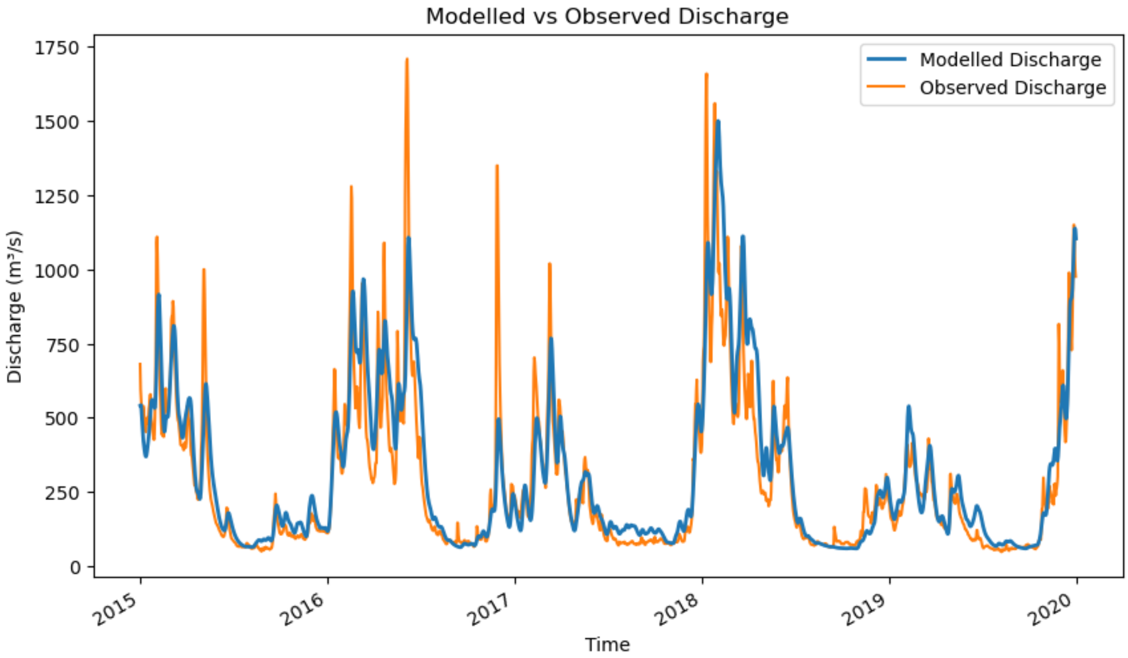

Figure 6: Visual validation of the modelled discharge for the period 2015-2019. In this graph, it is visible that the modelled discharge is correctly simulated for low water flows.

The model seems to have a good overall understanding of the river catchment. Yet, to fully assess the accuracy of the model, the droughts need to be analysed. The model error on the high flow peaks is not of interest.

The overview of *figure 7* displays the droughts for the calibration and validation period. Also, the relation between duration and deficit is plotted using a fitted first-degree polynomial.

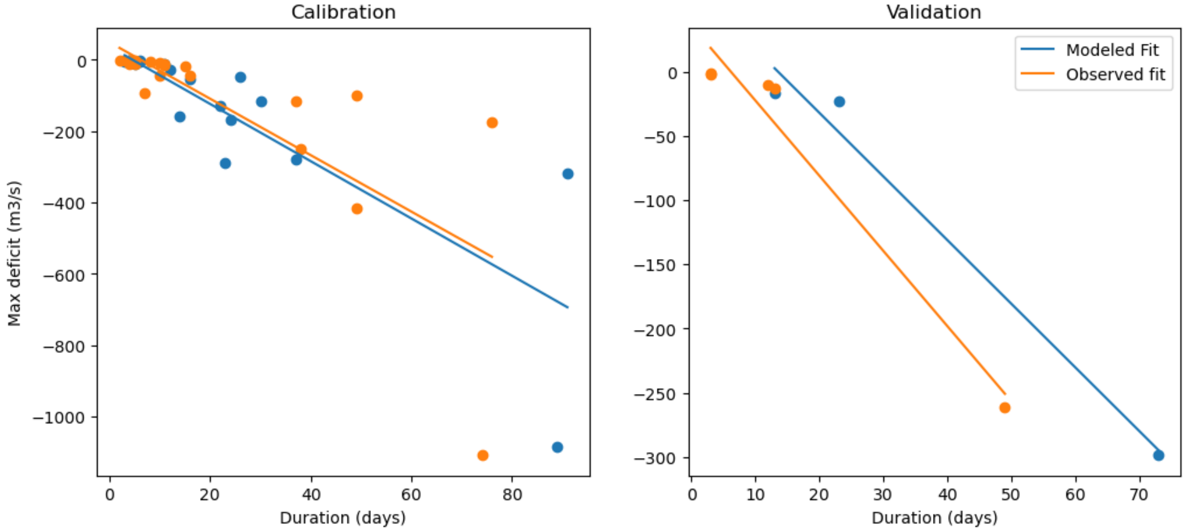

Figure 7: The relationship between droughts duration and deficit to validate the model using a first-degree polynomial. The model slightly overestimates the extreme droughts for both calibration and validation.

It is visible that model correctly detects the droughts in calibration and validation, yet there is a slight overestimation of drought severity and duration, especially for the validation period. The cause of this overestimation can be linked to the smaller size of data for this period. This is also visible in the distribution overview in *figure 8*.

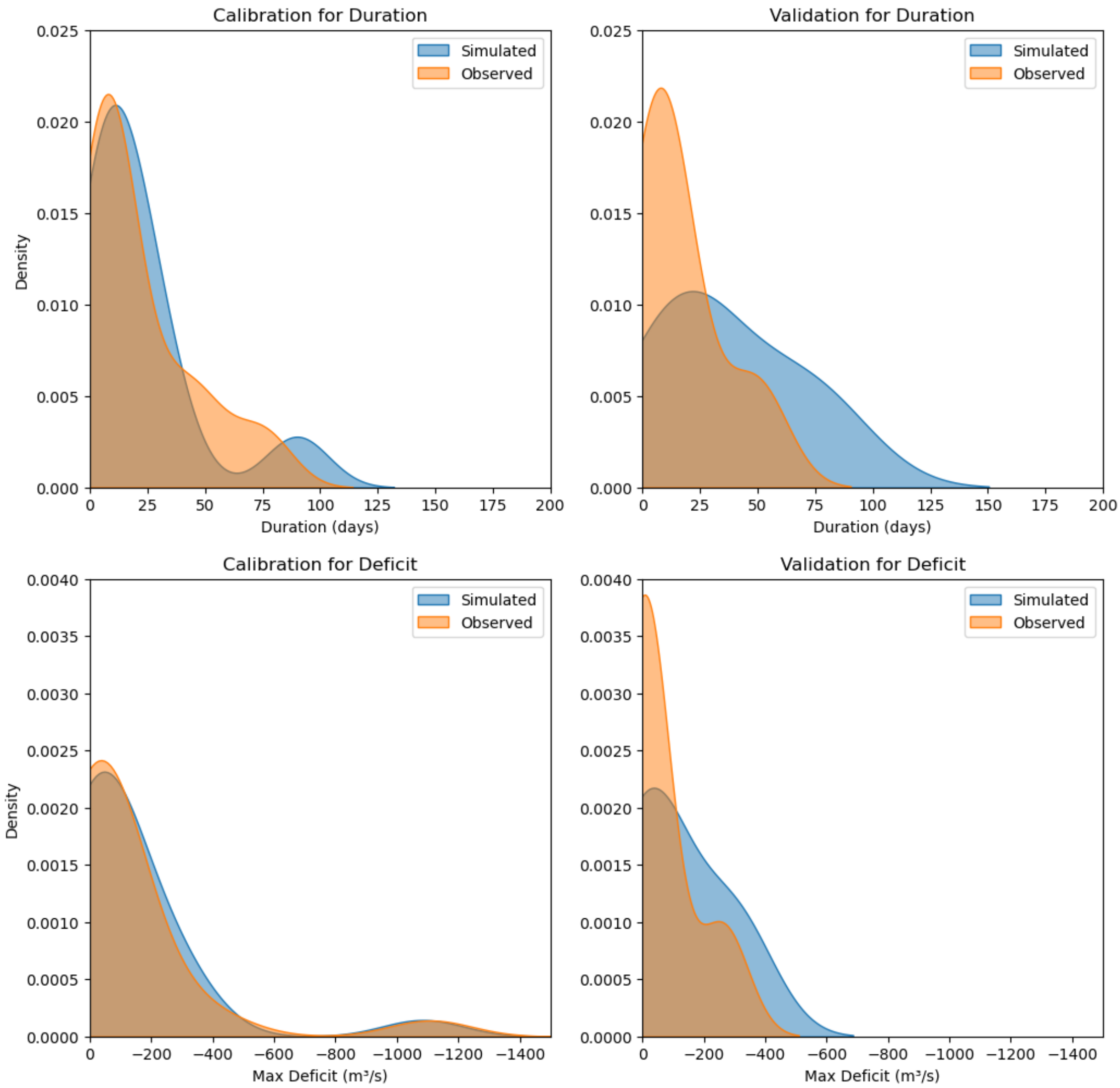

Figure 8: Distribution overview for calibration and validation. The left side of this overview displays the distributions for the calibration period, and the right side displays the validation period.

In the overview it is visible that in the calibration period, the modelled duration of the droughts gets slightly overestimated, yet the deficit is highly accurate. For the validation period of both duration and deficit, the distribution looks slightly inaccurate. However, this is caused due to a smaller sample size, where one minor drought was not detected by the model.

To conclude, the modelled output is acceptable since the overall functioning of the basin is properly represented. Also, droughts are properly detected, but for this research it is important to account for the fact that this model could overestimate certain drought events.

4 Future droughts

The prediction of future droughts is done by using the calibrated HBV model in combination with Coupled Model Intercomparison Project Phase 6 (CMIP6) 'MPI-ESM1-2-HR' data (CMIP, 2025).
To prevent potential error between ERA5 and CMIP6 forcings, historical droughts are also generated using CMIP6 forcings.

4.1 Climate scenarios

CMIP6 requires climate scenarios to generate forcings. For this research three Shared Socioeconomic Pathways (SSPs) are used as climate scenarios. These scenarios are used to better illustrate the impact of climate change under different future climate pathways and were chosen to represent the widest possible range of potential climate outcomes. The chosen scenarios are explained in *table 2*:

Table 2: Overview and explanation of the chosen climate scenarios (Riahi, et al., 2017).

Forcings	Scenario	Period: 72 years
Historical	Generated CMIP forcings from the past. This is based on historical observations processed by climate models.	1942 – 2014
SSP126	"Taking the green road": Where the world transitions into a sustainable future. There are low challenges for implementation of climate change mitigation.	2027 – 2099
SSP245	"Middle of the Road": Where the world continues in its current climate trend.	2027 – 2099
SSP585	"Taking the Highway": Where the development of the world is leaded by an increased use of fossil fuels. The world faces high challenges for climate change mitigation.	2027 – 2099

The periods of the forcings are chosen based on the available data from CMIP6. Historical data ranges up to 2014, and future forcings until 2100. To simplify the comparison of historical and future climate scenarios, the periods are the same length.

4.2 Future drought comparison method

After generating the forcings, the HBV model is used to predict discharge for the Loire River. The parameters for the HBV model are extracted from the ERA5 historical calibration and used for the CMIP data. The modelled discharges are then analysed by the drought analyser algorithm. The results of the algorithm are compared using a trend line between Duration and Deficit and the distribution for drought duration and deficit. Yet, these methods did not clarify the results, so another method is needed (see appendix B for these results). For this purpose, the cumulative distribution is used as it better displays the differences between the chosen forcings. The results are visible in *figure 9.*

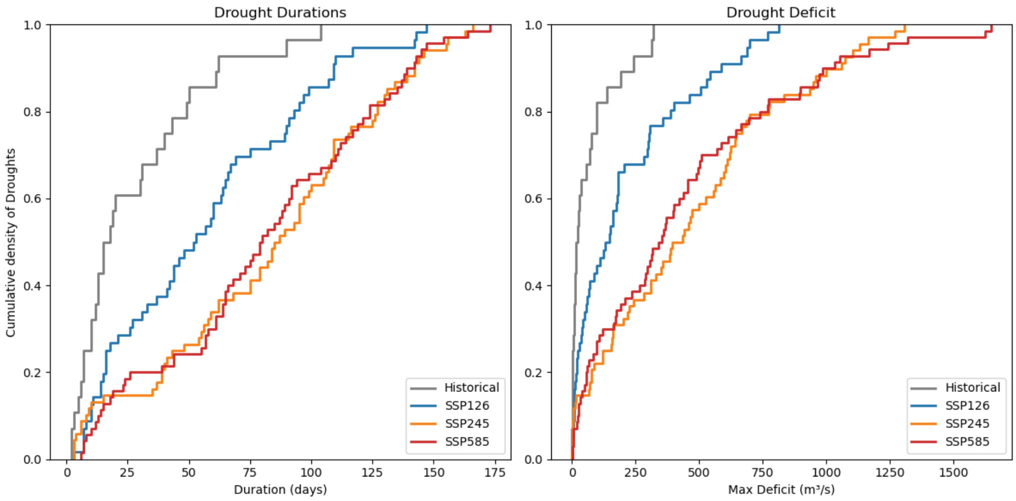

Figure 9: Cumulative distributions for Duration and Deficit. The graphs display the impact of the different scenarios. The distribution will go faster and further to the right, the more extreme droughts occur. This is especially the case for 'SSP245' and SSP585'.

The cumulative distributions clearly display the difference between the historical data and the future scenarios. As the scenario becomes more extreme, the droughts also become more intense based on duration and deficit.

These cumulative distributions are then used for quantifying the difference between historical and future droughts in terms of return period. This is achieved by using the drought return period function used by Zhao, et al. (2017):

$$T_D = \frac{N}{n\left(1 - F_D(d)\right)} \tag{5}$$

$$T_S = \frac{N}{n\left(1 - F_S(s)\right)} \tag{6}$$

The return period for duration is defined by T_D, and for severity (deficit) T_S. The length of the dataset is expressed by N, which is equal to 72 years. The number of drought observations is denoted by n. The cumulative distribution functions, which are displayed in *figure 9,* are defined by $F_D(d)$ for drought duration and $F_S(s)$ for drought severity (deficit).

To make sure that the modelled return periods are precise, the historical CMIP6 droughts are validated using the observed past droughts. The validation is displayed in *figure 10:*

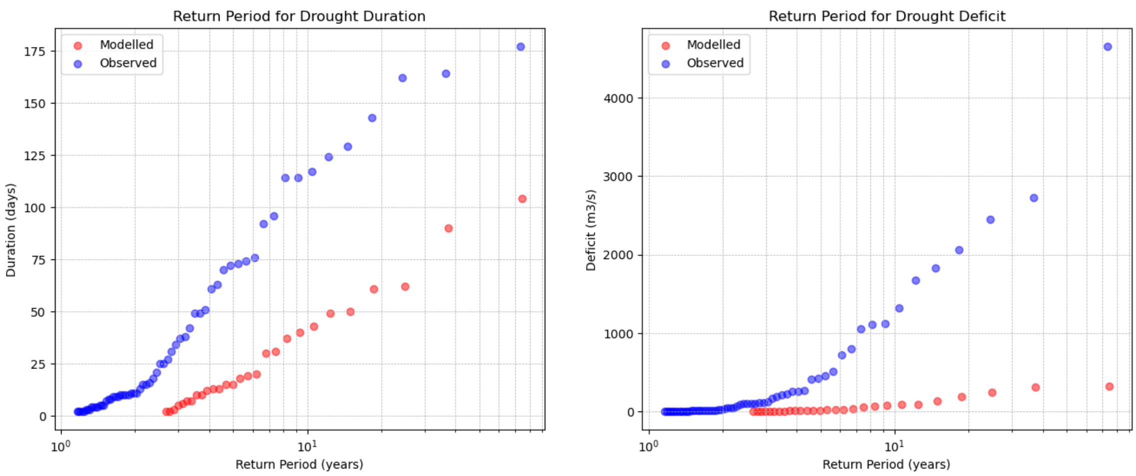

Figure 10: Validation of the return periods for 1942-2014. The graphs show a significant discrepancy for both drought duration and deficit.

The return period for observed and modelled droughts differ significantly. An explanaition for this is that the model is calibrated on the period of 1990 to 2019, yet the CMIP6 data ranges from 1942 to 2014. In the period between 1942 to 1990 stronger droughts occurred which the model did not account for due to limited historical ERA5 data. A correction factor could be used to compensate for this difference, yet this would mean that the return periods are corrected on droughts that occurred a longer time ago because of a lack of drought regulations. Major dams were only built in the 1980s (Moatar, et al., 2022). Therefore, this could lead to a distored comparison.

A better alternative is to define a correction factor based on the calibration period 1990 to 2014, so more recent droughts are represented correctly and the more extreme droughts before 1990 are adjusted on more recent data, making them more applicable.

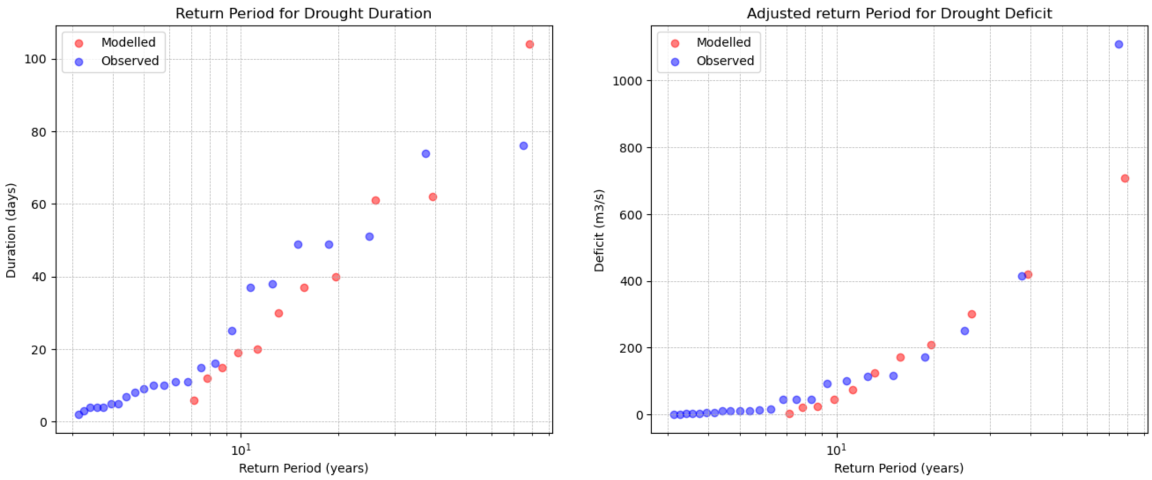

Figure 11: Correction of return period based on 1990-2014. For drought duration there was no correction factor needed. For drought deficit, a correction factor of 2.2 is applied.

The period of 1990-2014 shows less difference overall, which is expected. For the return period of drought duration no correction factor is applied as the model represents the observed values adequately. For the drought deficit there is a correction factor $CF = 2.2$ applied which was manually defined. The CF is already applied in *figure 11*. This results in an acceptable model representation for drought deficit. This correction factor is then used for the return period of all climate scenarios and historical modelled droughts. The return periods for drought duration are not adjusted.

5 Analysing results

In this chapter the results of the historical and future return periods are analysed. The return periods for each scenario are compared to the historical return periods, to conduct the impact of each climate scenario on droughts.

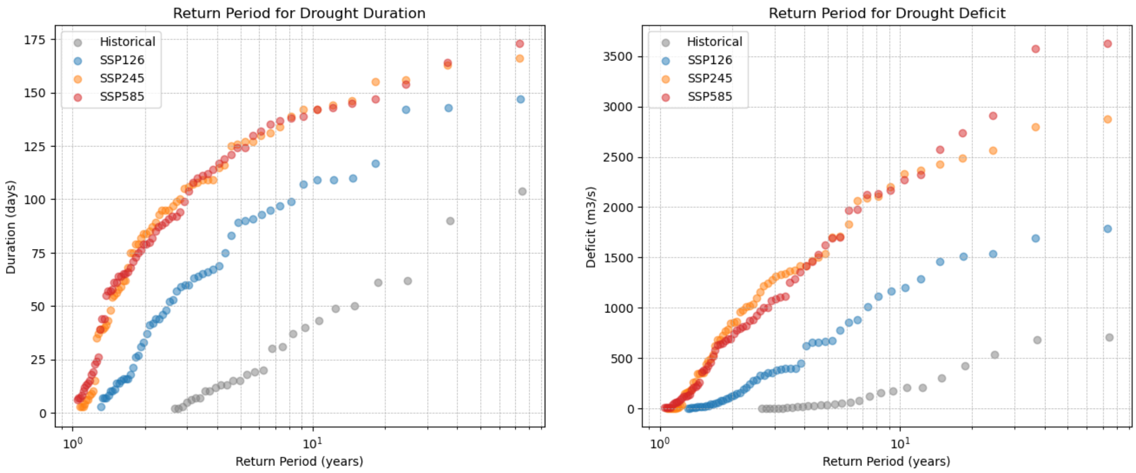

Figure 12: Return period for duration and deficit for all scenarios using the return period equations denoted in formula 5 and 6. For drought deficit, $CF = 2.2$ is applied.

In the figure above, it is evident that droughts are projected to become more extreme in terms of both duration and deficit. The return periods do not all start at 10^0, which is expected based on the return period equation (5) and (6). Since the return period is divided by the number of detected droughts (n), a larger number of detected droughts results in a smaller return period. Consequently, the historical return period has a higher starting point, as fewer droughts occurred in that period. This is confirmed by *table 3*, showing the number of droughts for each scenario:

Table 3: Number of droughts for each scenario over a period of 72 years.

	Historical	SSP126	SSP245	SSP585
Number of droughts	28	56	68	70

The duration and deficit are compared using a 10-year, 50-year and 100-year return period. A lower return period of 1-5 years is excluded, as these droughts have less impact on the basin. The results of the return periods are summarized in the table below:

Table 4: Overview of return periods for duration and deficit for each scenario. The increase is calculated based on the historical droughts.

Return period duration	**Historical**	**SSP126**		**SSP245**		**SSP585**	
	days	days	increase	days	increase	days	increase
10 years	42	108	157%	142	238%	141	236%
50 years	95	144	52%	164	72%	167	76%
100 years	114	150	32%	168	47%	180	58%
Return period deficit							
	m³/s	m³/s	increase	m³/s	increase	m³/s	increase
10 years	191	1187	521%	2289	1098%	2238	1071%
50 years	694	1729	149%	2824	307%	3594	418%
100 years	720	1861	158%	2936	307%	3664	408%

The results indicate that droughts with a 10-year return period are projected to become significantly more severe. For ‘SSP585’ this can go up to an increase of 236% in drought duration days. For 50 and 100 years this increase is smaller when droughts get more extreme. However, this can be explained by the fact that the Loire basin is a primarily pluvial hydrological system (Monteil, et al., 2010). In this system, extreme droughts typically begin in the summer months, and continue until the system is fully replenished. However, if a drought persists into the winter months, the system can recover more rapidly due to increased precipitation and reduced evapotranspiration. This explains that due to seasonal changes more extreme droughts have a smaller increase than less extreme droughts. This phenomenon is also noticed for drought deficit and confirms why a return period of 100 years does not increase as much as for 50 years.

There is also a clear difference between the chosen scenarios. “Taking the green road” ‘SSP126’ does indeed lower the drought intensity based on duration and deficit compared to ‘SSP245’ and ‘SSP585’, however there is still a strong indication that droughts will get more extreme under this scenario. The difference between ‘SSP245’ and ‘SSP585’ is minimal. There is no significant difference in drought duration, however drought deficit is expected to be more extreme under ‘SSP585’ scenario.

6 Discussion

This study aimed to assess the impact of climate change on drought characteristics in the Loire basin by analysing drought duration and deficit under different climate scenarios. In this chapter, these findings are interpreted using the sub-research questions defined in the objective of this research. Additionally, the limitations of the methodology and results are discussed.

The goal of the first research questions was to define the characteristics of droughts in the Loire basin. This was accomplished determining a critical water flow. Since the critical water flow for the chosen station had not yet been defined, it needed to be estimated. This estimation was based on mean monthly data from another station, as daily data was not available. Consequently, this approach may have resulted in a slightly inaccurate critical water flow, since daily fluctuations, which are important for defining a critical flow, were flattened out by relying on monthly averages.
Furthermore, droughts were defined based on duration and water shortage. While this definition provided a clear structure for quantifying drought severity, it may have excluded other relevant factors, such as river water temperature and groundwater influences.

The chosen model for this research was the HBV model. As mentioned in the calibration phase of this research, the model seems to have a good understanding of the hydrological system of the basin. For this research the model was sufficient since the model was reliable and easy to implement. More advanced hydrological models were not considered because of the limited research period and access on eWaterCycle. Nevertheless, implementing other models could have provided a useful comparison to assess the reliability of the HBV model.

The second and third sub-research question examined past and future drought occurrences in the Loire basin. Results indicated that historical droughts were less frequent and less severe compared to future projections. This aligns with findings from previous studies (e.g., Dayon et al., 2018 and Debein, et al., 2024) suggesting that climate change is expected to intensify drought conditions in the Loire catchment.

Furthermore, the reliability of the results could be further analysed since a correction factor was required to align the modelled droughts with the return period. A reason for this correction factor can be explained by bias from the CMIP6 forcings, as this model has known issues with simulating rainfall (Chai, et al., 2021). Consequently, this led to slightly different discharge values.
Additionally, only one ensemble member was used for the CMIP6 forcings. Exploring multiple ensemble members could provide more insight in the uncertainty of future droughts.

7 Conclusion and recommendation

To conclude, this research provides an answer to the main research question: ‘How will climate change influence future droughts on the Loire River?’ The results indicate that droughts will occur more often and become more severe under all climate scenarios. Even under a more favourable scenario ‘SSP126’ droughts become significantly more extreme compared to historical droughts.
However, the results of ‘SSP126’ show that climate change measures do mitigate future droughts compared to the climate scenarios where less measures are applied (‘SSP245’ and ‘SSP585’).
The difference in drought duration between ‘SSP245’ and ‘SSP585’ is minimal. This can be explained by seasonal precipitation patterns in the Loire basin, as winter months appear to act as a natural reset, replenishing water levels and preventing droughts from extending indefinitely. For deficit, ‘SSP585’ droughts will only become more extreme under higher return periods compared to ‘SSP245’.

However, only one ensemble member for CMIP6 is used to predict future droughts due to a limited research period. This results in increased uncertainty regarding the predicted drought results. For future research it is recommended to explore multiple ensembles to gain a better understanding of the uncertainty range for future droughts.
Additionally, only one hydrological model was considered for this research. While the HBV model provided reasonably accurate discharge data, it showed a moderate overestimation on drought duration and deficit. This may be linked to the limited calibration and validation period. Comparing multiple models could provide more insight in the application of the HBV model for this catchment.

Despite these limitations, this research offers valuable insights into future drought trends in the Loire basin. Further research is recommended to assess the potential impact of future droughts on water availability for agriculture and nuclear power plants. This would help determine whether additional drought mitigation strategies are necessary to ensure water security in the basin.

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Appendix A: Drought analyser

```python
def drought_analyser(df, basin_name, q_crit):
    droughts = []
    drought_counter = 0
    i = 0

    while i < len(df):
        if df.iloc[i] <= q_crit:
            drought_counter += 1
            days_counter = 0
            deficit_list = []
            cum_def_list = []
            accum_deficit = 0
            max_cumulative_deficit = 0
            start_date = df.index[i]

            while i < len(df):
                deficit = df.iloc[i] - q_crit
                deficit_list.append(deficit)
                accum_deficit += deficit
                cum_def_list.append(accum_deficit)
                max_cumulative_deficit = min(max_cumulative_deficit, accum_deficit)
                days_counter += 1
                i += 1

                if accum_deficit > 0:
                    break

            if max_cumulative_deficit < 0:
                droughts.append({
                    "Drought Number": drought_counter,
                    "Start Date": start_date,
                    "Duration (days)": days_counter,
                    "Max Cumulative Deficit (m3/s)": max_cumulative_deficit,
                    "Cum Deficit List": cum_def_list
                })
        else:
            i += 1
    if drought_counter < 1:
        droughts.append({
                "Drought Number": 0,
                "Start Date": df.index[0],
                "Duration (days)": 0,
                "Max Cumulative Deficit (m3/s)": 0,
                "Cum Deficit List": 0
            })

    return pd.DataFrame(droughts)
```

Appendix B: CMIP results