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Course number:	GEO4-1520
ECTs:	30
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5-18-2023

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The historical and future effects of Environmental Flow Requirements on hydrologic indicators and water scarcity in the Danube River Basin

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Abstract - Extreme low-flow conditions have a detrimental effect on aquatic life in freshwater systems. The chance at low-flow conditions is expected to grow as a result of climate change and increased human demand. The European Union is advising its member states to implement Environmental Flow Requirements (EFRs). The Danube, with its great importance and size, is a fitting case study for the implementation of EFRs. This study used the PCR-GLOBWB 2 model, at 5" arcmin scale, to analyse the effectiveness of EFRs based on changes of hydrologic parameters and the impact on water scarcity. This was done for a monthly timeframe to determine the influence of seasonality. Two different EFRs have been studied: the Variable Monthly Flow and the 90th exceedance percentile. The WATCH dataset supplied validated data to study the changes in water scarcity levels and hydrologic parameters as a result of EFR inclusion for the period from 1960 till 2000. Subsequently, the model was forced precipitation and evapotranspiration data from 5 bias-corrected Global Circulation Models, for the RCP 6.0 scenario, in order to study EFR effects on the near (2010-2050) and far (2060-2100) future. The results show an improvement in drought related indicators, namely minimal annual flow and extreme low-flow (Q95), with the implementation of EFRs with the WATCH Forcing Data. This improvement is most distinct in the Hungarian low-lands where without regulations abstractions are responsible for a significant decrease in IHA performance. As water is reserved for the environment, competition over available water resources is enhanced. The EFR definition can have a significant impact on the temporal and spatial distribution of periods of water scarcity. Model runs based on GCM forcing did not show significant IHA improvement related to EFR inclusion, but water scarcity was is expected to exacerbate with time.

1. Introduction

Drought induced low-flows can have dramatic impact on riverine life and the surrounding environment. Low-flows are associated with poor water quality, because less dilution leads to higher levels of pollution. Simultaneously the amount of oxygen in the water drops, resulting in death of aquatic life (Humphries and Baldwin 2003). While population growth results in higher water demand, climate change could lead to more persistent dry periods (Bisselink, de Roo, et al. 2018; Unesco 2018). Consequently competition for water is expected to grow (Boretti and Rosa 2019), thus increased withdrawals will threaten the health of rivers and surface waterbodies by increasing the likelihood of severe low-flow events. As the quality of rivers continues to decline, European authorities are initiating programs to reverse this trend (European Commission 2000; 2016).

One of the ways through which bodies of power try to impose regulations on rivers and waterbodies is by implementing Environmental Flows Requirements (EFRs) (European Commission 2016). To regulate the quality and quantity of water, a profound understanding of the local hydrology is required. Often in hydrology an area of study comprises a catchment area – a region where water flows towards the same outlet. However, the catchment might encompass a multitude of different authorities, as is the case for transboundary river basins. As a result, imposing and maintaining EFR can be complicated. Within the European Union, EFRs are embedded within the Water Framework Directive aims to protect and promote the sustainable use of its water resources. While this sets a EU-wide directive, the definition of the EFR is still open for interpretation and this remains a major challenge.

EFRs can be based on data with different complexity: an environmental flow based solely on hydrologic data is more simplistic while including water quality, temperature and/or biologic measurements results in a more holistic approach (Pastor et al. 2014). There is a wide variety of ways in which EFRs can be established. As a result it can be difficult to determine which is the best fit for a particular basin or river. However, hydrologically based initiatives are most common (Tharme 2003).

This study will focus on EFR inclusion for the Danube River Basin. The Danube River Basin is spread across many countries, each with their own legislature. When one of the upstream countries, like Austria, builds a dam for hydro-power this can affect will affect the water supply for all downstream areas up till the lowlands of Romania. Furthermore, with the Danube as study region there are varying climatology's and topographic differences. As a result the flow regimes vary between the tributaries, the flow regime is used to determine the EFR and one methodology for EFR formulation might fit one type of flow regime better than the next. As there is no clear consensus within the scientific community on a single EFR formulation, two common definitions of EFRs will be analysed and compared. While a lot of research has focused on the formulation of EFRs and the ways EFR demands can be met, the direct effect of the enforcement of EFRs on competition over water is not well understood. Because EFRs limit the water available for human use, their inclusion will increase competition over water. The impact of widescale EFR implementation throughout the Danube River Basin will be studied through analysis of hydrologic- (IHA) and drought (WEI+) parameters. Will inclusion of the EFRs result in improved hydrologic conditions, and if so, does this weigh against the enhancement of competition over water?

The basis of this study is the large-scale water resource model PCR-GLOBWB (van Beek and Bierkens 2009; Sutanudjaja et al. 2018) that incorporates the supply and demand sides of the global water balance. In this study, PCR-GLOBWB was applied for the Danube River with a spatial resolution of 5 arc minutes (5') and a daily temporal resolution. The historical period ranges from 1960 till 2000 and uses WATCH Forcing Data (Weedon et al. 2011). The Representative Concentration Pathway 6.0 (RCP6.0) supplied climate forcing data for model runs that simulated the future (van Vuuren et al. 2011). A historic dataset from the RCP6.0 scenario was used to analyse the differences with WATCH data in order to determine any biases that were left after correction. To account for the uncertainty in the effects of anthropogenic greenhouse gas emissions on the resulting climate and weather patterns, bias-corrected output of five general circulation models was used from the ISI-MIP 3 project (Warszawski et al. 2014). The model runs for the future were split into two timeframes, one regarding the near future (2010-2050) and one for the far future (2060-2100). The middle of the road narrative, Socio-economic Shared Pathway 2 (SSP2), was used: population, land-use and water demands vary between the historic, near- and far-future runs (Riahi et al. 2017). Water scarcity will be effected by changes in land-use and water demand, which will compound with the effects of climate change.

While there are projects that couple hydrologic quality measures, like water temperature and pollution load, to PCR-GLOBWB with DynWat and DynQual (Jones et al. 2022) allowing for a more holistic approach, because of time constraints this study opted for an EFR based solely on hydrologic characteristics. During this study a dedicated module was added to PCR-GLOBWB 2 to prescribe EFRs. From here onwards PCR-GLOBWB 2 will be referred to with PCR-GLOBWB and no distinction will be made. The 90th Exceedance percentile (Q90) and Variable Monthly Flow (VMF) were used to formulate the EFR as both are able to determine an environmental flow based on hydrologic data alone. Furthermore, VMF was created to function properly for a different flow regimes in order to be viable for large scale modelling (Pastor et al. 2014). The Q90 was suggested by Bisselink, Jacobs, et al. (2018) as a more appropriate means to implement the EFR (than 1m^3/s, or Q95). Other studies opt for a different form: Q90 during low-flow season and Q50 during periods of high flow (Gopal 2013; Bisselink, Jacobs, et al. 2018). However, some concern surrounds the size of Q90, as it is deemed low-flow and therefore might not suffice to meet environmental demands (Gopal 2013).

In order to measure the hydrologic impact of the EFR a selection of indicators of hydrologic alteration (IHA) have been used. The indicators were largely based on the IAHRIS model (Martinez Santa-Maria et al. 2008), with some modifications to incorporate monthly variations. For analysis of the water scarcity a variation of the Water Exploitation Index plus (WEI+) was used (Casadei, Peppoloni, and Pierleoni 2020). For the IHAs, hydrologic flow aspects are measured in environmental and altered state. The difference is then converted to a parameter of change. The more a flow has been altered, the lower the value of the parameters. One of the concerns with EFR implementation is the lower water availability for human demand, which results in higher water scarcity. If the proportion of renewable water consumed for human interests increases, so does the WEI+ value, and this can be used to analyse the effects of the EFR.

EFRs are seen as a measure to safeguard the original flow regime of a river (Tharme 2003). It is difficult to formulate an EFR capable of protecting every aspect of a rivers flow regime, let alone regulate it for a transboundary river system. However, this study is mainly focussed on limiting low-flow conditions for rivers. Implementation of an EFR would limit the amount of excessive withdrawals, and safeguard some water for the natural environment. In light of the EU's Water Framework Directive and because of its transboundary nature, the Danube River, Europe's second largest river, with its wide range of environmental conditions and human activities, forms an intriguing case. In recent years, the Danube River Basin has been hit with a series of droughts (Jakubínský et al. 2019). Climate change is expected to exacerbate this problem, forcing policy makers to start adapting (Gregorič et al. 2019). Currently, no preliminary measures are in place and warnings are carried out only when the impact is already visible. Due to its prominence, the Danube has been the subject of many hydrological studies focusing on water scarcity (Ionita, Scholz, and Chelcea 2015; Bisselink, de Roo, et al. 2018; Gregorič et al. 2019; Jakubínský et al. 2019), floods (Dankers et al. 2007; Hattermann et al. 2018) and the ecosystem (Garnier et al. 2002; Karabulut et al. 2016; Stagl and Hattermann 2016). However, the effects of an EFR on water scarcity and flow characteristics for future scenarios in the Danube river catchment have not yet been studied.

Summarizing, in line with the overall objective, this study shall (1) implement and apply different, common definitions of the EFR from literature, namely the Q90 and VMF in a hydrological model, and (2) evaluate their impact on the simulated hydrological behaviour with particular focus on the competition for water during periods of drought. This was done for a historic period (1960-2000) and under scenarios of plausible near (2010-2050) and far (2060-2100) future scenarios due to human-induced climate change and projected socio-economic developments.

2. Methodology

2.1 Study area

The Danube River Basin stretches across 19 different countries and has a total surface area of more than 800.000 km^2 (Ionita, Scholz, and Chelcea 2015; Karabulut et al. 2016). The river basin houses 83 million people and plays an important role for many different aspects of human life by supplying water for households, for the irrigation of crops or for manufacturing (ICPDR 2022). Furthermore, it allows for extensive energy production, both throughout hydropower and thermal cooling (REKK 2020). These different sectors are spread across the Danube, with hydropower having a large presence in the headwaters and agriculture mainly in the low-lands of Hungary and Romania. As a results of the Danube spatial extent a variety in climates and accompanied flow regimes can be found. The upper reaches near the Alps have significant amounts of precipitation, between 1000 and 2800 mm per year, while Romania and Bulgaria have low precipitation rates between 300 and 800 mm per year (WATCH Dataset). As these areas of relative low precipitation are widely used for agriculture, they have a direct dependence on irrigation from head waters, the main Danube or, if none is available, groundwater. As a result these regions are at risk of crop failure (Páscoa et al. 2020), and powerplants could have to cease production if no water is available for cooling which results in decreased energy production (van Vliet et al. 2016).

Figure 1: Topographic overview map of the Danube River Basin. Shows all major tributaries and gives an impression of the land. Map was created by the ICPDR and can be found at: danubegis.org.

The population of the Danube is expected to shrink in size, except for the Pannonian Danube where urbanisation leads to population growth (Bisselink, de Roo, et al. 2018). However, demand for water continues to rise, mainly coming from increased energy use which requires water for cooling, throughout large parts of the basin (Bisselink, de Roo, et al. 2018). Furthermore, larger regions will experience difficulties with water supply as climate change is expected lower the amount of runoff during summer periods (Ionita, Scholz, and Chelcea 2015; Stagl and Hattermann 2015; Bisselink, de Roo, et al. 2018). Partly as a result of less rainy days (>1mm / day) and furthermore as a result of higher temperatures leading to decreased snow storage and earlier melt. These climatologic and socio-economic developments present a challenge for water managers throughout the entirety of the Danube.

The International Commission for the Protection of the Danube River (ICPDR) was formed to lead research and help manage the river basin. Its contractors are the European Union and the 14 countries with more than 2000 km^2 of land in the basin (Karabulut et al. 2016; ICPDR 2022). In order to protect the environment from this increased vulnerability to periods of drought the EFR is meant to alleviate some of the stress on nature. This study uses the management plan along with the Guidance Document No 31 of the Water Framework Directive as guidance when establishing the EFRs (European Commission 2016; ICPDR 2021).

2.2 Environmental Flow Requirements

The Environmental Flow is one of the measures through which the ICPDR is able to protect the water availability for nature. However, determining the right methodology is not clearcut. At the start of this century, already more than 200 methodologies existed (Tharme 2003), and more have been created since (Pastor et al. 2014). In this study two methods of EFR determination have been selected, based on the data and time-availability for this project: the Variable Monthly Flow method and the 90th percentile approach (Q90).

The VMF method, created by Pastor et al. (2014), has been selected as it was designed and tested to define a functioning EFR for hydrologic modelling in a study area with a variety of flow regimes. In order to compare its performance, a generally accepted and easy to implement EFR, the Q90, was additionally investigated during the historical runs of the study (Bisselink, Jacobs, et al. 2018). These only require hydrologic data and can easily be applied at scale. These methods are within the terms of the Water Framework Directive, as they are scientifically based, with a large spatial extend and with hydrologic data available only (European Commission 2016). For the Q90 method the environmental flow uses the average monthly flow that is exceeded 90% of the time (Q90). The value of Q90 can vary largely between locations, as a downstream river might have a constant supply of discharge from a variety of headwaters, resulting in a consistent stream, while headwaters are more dependent on rains and might have periodic low- or no-flows. The VMF uses the Mean Monthly Flow (MMF) and the Mean Annual Flow (MAF) to first determine the flow regime for each month. The monthly flow regime determines the quantity of water reserved for the EFR. This varies between 60% during low flow months, and 30% during high flow months (see table 1).

Table 1: Description of the amount of water reserved for the environmental flow. MMF: Mean Monthly Flow.

Flow Category	*Mean Monthly Flow Size*	*Environmental Flow Req.*
Low Flow	MMF < 0.4 MAF	60% of MMF
Intermediate Flow	MMF > 0.4 MAF & MMF <0.8	40% of MMF

	MAF	
High Flow	MMF > 0.8 MAF	30% of MMF

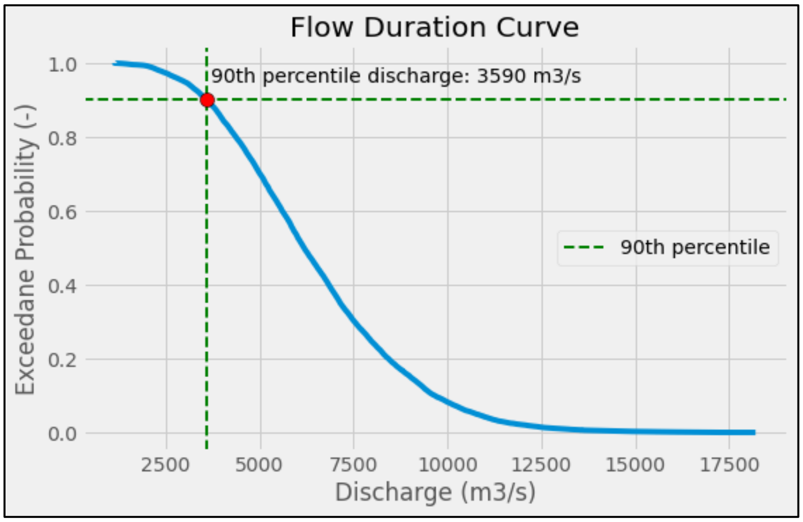

Figure 2: Example of a flow duration curve, in this case the value of Q90 would be 3590 m3/s as more than 90% of the time the discharge is higher than this value.

2.3 The PCR-GLOBWB Model

The PCR-GLOBWB model is a hydrologic model that allows the simulation of water demand and supply globally. It incorporates a wide variety of dynamics related to the atmosphere, surface and groundwater, visible in figure 3 (Sutanudjaja et al. 2018). An environmental flow module was added to the PCR-GLOBWB model, which is capable of implementing different definitions of EFRs through a set of generic parameters (see 2.3.1). Once the EFRs are defined the available water for abstraction are limited accordingly. This inhibits water abstractions when environmental limits are reached.

The EFR will have direct effect on a few of the processes within PCR-GLOBWB, most notably the water abstractions for ground- and surface water, and the interaction between these water sources. PCR-GLOBWB uses allocation cells, water demand within one of these cells is met by water that is available within this allocation cell. This might result in a local city not being able to access water from a nearby lake because it might be situated just outside its cell. The most important thing in regards to the interaction between these abstractions and EFR, is that limitations as a result of EFR inclusion in one waterway may result in increased abstractions in another waterway to be able to meet local demands. If not enough surface water is available, this may result in exacerbate groundwater extraction. This can in turn influence the interaction between ground and surface water by diminishing basal flow and increasing the amount of infiltration.

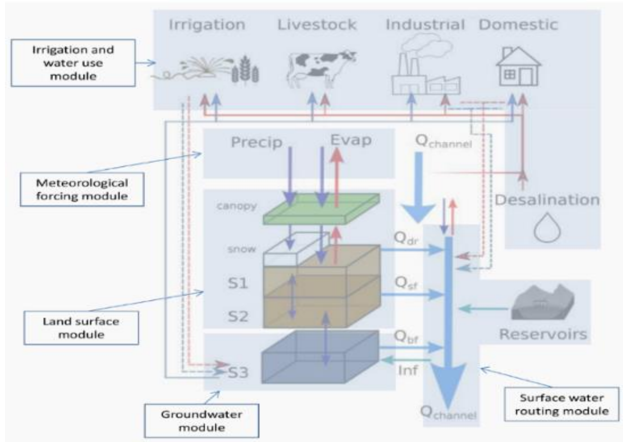

Figure 3: Schematic of the dynamics encompassed by the PCR-GLOBWB model, taken from and in detailed explained by Sutanudjaja et al. (2018).

2.3.1 The Environmental Flow Module

Large scale modelling is capable of determining the influence of EFRs for an entire basin within a relatively short timeframe. So far, environmental flow research is mainly focused on surface water (Pastor et al. 2014; Jägermeyr et al. 2017; Bisselink, de Roo, et al. 2018; Bosmans et al. 2022), with minimal ventures into groundwater systems (Esteller and Diaz-Delgado 2002; de Graaf et al. 2019). While groundwater is of importance, it was infeasible to implement an EFR to groundwater withdrawals within this study. From the hydrological data gathered in the environmental scenario (1) the Mean Monthly Flow (MMF) and Mean Annual Flow (MAF), which are required to calculate the VMF, and the Q90 were calculated. The discharge, slope and width of the channel are used in combination with Manning's coefficient to calculate the water height (see equation 1). The amount of water situated at any timestep in a channel in PCR-GLOBWB is expressed in meters of water height. The EFR is meant to reserve a certain amount of water for the environment. In order to make the EFR and channel storage compatible a conversion from discharge, which is in cubic meters per second, to height has to be performed (Eq. 1).

$$h = \left(\frac{nQ}{B\sqrt{s}}\right)^{3/5} \qquad Eq. 1$$

With h being the water height (m), n being the Manning's coefficient (-), Q is the flow (m3/s), B is the width of the riverbed (m) and s is the slope (m/m).

To create some flexibility in the amount of water reserved by the EFR, a two-step system was implemented, with a hard and a soft limit. This way, during periods of high demand, more water would be admitted for possible withdrawal. Once the hard limit (h_{hard}) is exceeded no more water may be abstracted under any circumstances. The water is already below the environmentally acceptable limit implemented. The soft limit varies per month, and is in this study based on the monthly 90th exceedance percentile, the section water between the hard and the soft limit (h_{soft}) that will be available for abstractions depends on the amount of water demand.

$$h_{res} = h_{hard} + \left(h_{soft} - h_{hard}\right) * \max\left(0,\ \ 1 - 0.5 * \frac{h_{claim}}{h_{soft} - h_{hard}}\right)\ if\ h_{soft} > h_{hard} \qquad Eq. 2a$$

$$h_{res} = h_{hard} \qquad if\ h_{soft} \leq h_{hard} \qquad Eq.2b$$

The ratio between the hard and soft limit determines the equation. Any height between an upper soft limit and a lower hard limit will be admitted to human demand at a reduced rate (Eq. 2a). If the soft limit is found below the hard limit, it is not of influence and only the hard limit is saved for the environment (Eq. 2b). The amount of water available for human use rises linearly with the demanded water height (h_{claim}). The h_{res} is the amount of water reserved in meters height, both the soft and hard limit as well as the water demand height have the unit meters height.

The two-step system is used for the Q90 methodology, with the hard limit set at the lowest monthly value of the 90th flow percentile and the soft limit as the 90th monthly flow percentile itself. As a result, the hard and soft limit coincide for the month with the lowest 90th percentile value. For the VMF only a hard limit was put in place at the assigned monthly VMF value. For both the Q90 and VMF methods a flow of 1 m^3/s was assigned as the global minimal value for the hard limit, as abstractions in an area with less than 1 m^3/s of flow are assumed to be neither technically likely nor desirable.

2.3.2 Model scenarios

The study of EFR influence on the Danube was divided into two sections that would later be studied in comparison. The initial stage consists of 4 model runs based on atmospheric forcing data from the WATCH dataset. The WATCH Forcing Data is widely used throughout the scientific community. It is considered to provide a proper estimate of climatologic trends and meteorologic events over the timespan of 1958-2001, and was created for large scale modelling as is required in this study (Weedon et al. 2011). The second stage consists of 20 model runs and is based on forcing data supplied by climate models and a socio-economic narrative. For each time-period and climate forcing there would be one scenario with EFR inclusion, and one business as usual (or baseline) scenario. The timespan for every model is set at 40-years to achieve a balance between longer and shorter time periods that are more robust and precise, respectively (Khaliq et al. 2009)

The World Climate Research Program (WCRP) has provided models through the Coupled Model Intercomparison Project (CMIP), that generate climate forcing data. From the CMIP5 the following Global Circulation Models were selected, in line with the ISI-MIP framework, to cover the total range of climate models: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, NorESM1-M. The datasets from these Global Circulation Models where calibrated to match the mean and standard deviation of the WATCH. These models were completed for different forcing scenarios, ranging from 2.6 to 8.5 W/m^2 at the end of the 21st century. For this study the 6.0 W/m^2 forcing scenario was used, as this is expected to be an optimistic average. For the narrative regarding socio-economic developments the Socio-economic Shared Pathways (SSPs) were created by the scientific community (Riahi et al. 2017). Five different scenarios were created: (1) Sustainability, (2) Middle of the Road, (3) Regional Rivalry, (4) Inequality and (5) Fossil-fuelled Development. Full explanation of each scenario can be found in the overview paper of Riahi et al. (2017), for this study the SSP2: Middle of the Road was used. It fits the radiative forcing 'average' scenario. The SSP determines land-use, water demand and energy needs (Riahi et al. 2017). This determines for each cell the water demand per timestep in PCR-GLOBWB.

For the model runs most of the standard PCR-GLOBWB settings are kept, with some general adjustments, and some model run specific adjustments. All model runs happen for the same study region. Between model runs the atmospheric forcing data will be changed. The atmospheric data used in these model runs is supplied at 30 arcmin, and can be downscaled with PCR-GLOBWB to 5 arcmin if desired at the cost of additional computing power and require some additional information (Sutanudjaja et al. 2018). In general the model functions at 5 arc min, as a result the same precipitation and evapotranspiration values are given to all cells within a 30 arc min region, only temperature was downscaled. Temperature plays a significant role by determining when rain turns into snow, local variations in precipitation and evaporation were deemed of lesser interest. As the for the climate forcing models there is no data available prior to 1960, the time period that will be covered spans from 1960 till 2000 instead of model runs with the WATCH dataset that range from 1958 till 2000.Furthermore, between the historic and the future runs, there is a change in water demand from each of the sectors (industry, agriculture, livestock and domestic). Corresponding data from the SSP2 was made available by E. Sutanudjaja who collected this data from Riahi et al. (2017) and Fricko et al. (2017).

To create a situation that resembles the actual initial conditions within the Danube River Basin, a model run of 10 years was completed. At the start of this run, no water was stored in reservoirs or aquifers. By simulation 10 years of processes, the storages can reach a level where equilibrium occurs. As a result, the actual model runs will have a more accurate representation of reality. The spin-up run was completed with natural conditions, this means no human abstractions or manmade reservoirs. The output of the final timestep of this run was used as initial conditions for the environmental run. For the runs with human interaction, a separate spin-up run was completed with human interactions, spanning the same 10 year period. It should be noted that this spin-up period still includes a bias, as the period used to create the initial storage might not be representable for the storage as a result of many years prior. However, the same initial conditions are used across the model runs, with an exception for the historic environmental run, this should not be of significant influence on the study results.

At first a Pristine (1) run was completed. The Pristine scenario entailed only natural processes, no anthropogenic reservoirs, withdrawals or return flow was included. The discharge data from this run would be used to define the quantity of the EFRs. Additionally, it would be used during the calculation of the IHAs as this is considered the original flow regime in this study. The second run was the Historic Baseline (2) scenario, which represents the original situation during the period between 1958-2000. In this scenario the EFR is not yet included. The first effects of the EFR would be analysed based on the Historical Variable Monthly Flow (3) and the Historical Q90 EFR (4) scenario. The only difference between these two runs and the prior baseline run is the implementation of the EFRs. For the Q90 methodology a hard and soft limit have been applied as discussed in section 2.3.1, for the VMF only a hard condition is given. These runs allow the comparison of the effectiveness of different EFRs have on water scarcity, river performance and the times EFR limits are exceeded. The values for the VMF and Q90 EFR are determined once, and have a value for each month. While the river regime might change as a result of climate change, this will not impact the definition of the EFRs.

The second stage consists of model runs forced with atmospheric data that originates from GCMs. The Historic GCM Baseline (5) and Historic GCM Variable Monthly Flow (6) scenarios allow comparison with the WATCH dataset. It shows if there are any major difference that occur as a result of the forcing data. If this is the case, these difference can also be expected in exacerbated amounts for the future. The settings for these scenarios were identical to the Historic Baseline (2) and the Historic Variable Monthly Flow (3) scenarios, except for the forcing data used. Because five GCMs are used as forcing data, the amount of model runs within a scenario also multiplied five fold. To save time only the VMF was included for the model runs of 2006 till 2100. Lastly the impact of the EFR was analysed based on the Future GCM Business As Usual (7) and the Future GCM Variable Monthly Flow (8) scenarios. The future scenarios made use of the data supplied by SSP2.

Table 2: Overview of the scenarios. Every time period has at least one Business As Usual and a Environmental Flow scenario to analyse the effects of the EFR.

ID	*Model Run*	*Time period*	*Environmental Flow*	*Forcing*
1	Pristine	1958-2000	None	WATCH
2	Historic Baseline	1958-2000	None	WATCH
3	Historic Variable Monthly Flow	1958-2000	VMF	WATCH
4	Historic Q90 EFR	1958-2000	Q90	WATCH
5	Historic GCM Baseline	1960-2000	None	GCMs*
6	Historic GCM Variable Monthly Flow	1960-2000	VMF	GCMs*
7	Future GCM Business As Usual	2006-2100	None	GCMs*
8	Future GCM Variable Monthly Flow	2006-2100	VMF	GCMs*

*Includes the: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M model

2.4 Evaluation of the water resources

In this study we evaluate the hydrologic situation mainly in three ways at a monthly timescale. First off, the quantity of renewable water is analysed for every cell – water use must remain within the boundaries of the renewable water to function sustainably. Secondly, the hydrologic parameters known as Indicators of Hydrologic Alteration, adapted from Martinez Santa-Maria et al. (2008), will show changes in the flow regime. Lastly, the use of a modified WEI+ parameter for water scarcity makes it possible to evaluate the impact of EFR inclusion on water scarcity and competition over the available resources. The WEI+ was calculated for subbasins while demand from one cell may be sourced in another, as long as it is within one allocation cell. Allocation cells have a larger size than the regular grid cells. The monthly timescale allows fluctuation between the months linked to seasonality both in climate and in demand.

2.4.1 Renewable water and limits

The quantity of renewable water resources (RWR) is a key factor for long-term well being of civilization. Renewable water is considered the water delivered to a region within a set timeframe by natural processes. Exploiting water resources post the rate of these renewable water resources will eventually cause the destruction of the local water balance. By implementing an environmental flow, we protect the rivers from over-exploitation, yet the resources available to meet human demands.

Within our model the renewable water resources are analysed for individual cells, as a result the water balance is determined by a few factors (Eq. 3): the net atmospheric flux (Q_{atm}), groundwater flow (Q_{gw}) and runoff (Q_s) from adjacent cells (van Beek, Wada, and Bierkens 2011). The net atmospheric flux is defined as the amount of precipitation minus the evapotranspiration. As evaporation cannot exceed the amount of available water, in general within a system there will be more precipitation than evaporation. However, at cell level a evapotranspiration surplus might occur, as a result there the amount of renewable water resources diminishes. Groundwater and runoff will enter a cell from adjacent upstream cells. However, it should be noted that if all renewable water is used within a cell, there will be no runoff entering the downstream cell. Therefore, for the entire catchment the renewable water that is generated per timestep is simply the balance between the precipitation and evaporation.

$$\mathrm{RWR}_{cell} = \mathrm{Q_{atm}} + \mathrm{Q_{gw}} + \mathrm{Q_s} \qquad Eq.3$$

While this study is mainly focused on the effect EFR inclusion has on the competition over water resources, at present and in future scenarios, it should be noted that climate change will heavily effects the renewable water resources within the catchment. Especially at a seasonal scale the quantity of available renewable water will change. If water can be trapped within the system during periods of water surplus, spring for example within the Danube, it would be possible to compensate the summer deficit.

2.4.2 Indicators of Hydrological Alteration

Indicators of Hydrologic Alteration have been used to determine the morphologic alteration within a waterway (Martinez Santa-Maria et al. 2008). However, in this study these parameters provide a measure of environmental well-being. Furthermore, these parameters show how much the new flow regime has changed from its baseline (equation 4). The parameters used in this study have been adapted from the IAHRIS model (Martinez Santa-Maria et al. 2008). The abbreviations IHA and IAH can be used interchangeably, representing Indicators of Hydrologic Alteration and Indicators Alteration Hydrologic respectively. As the original software required Microsoft Excel 2003, and was meant for analysis of individual streams , this format was replicated within a bash script using primarily Climate Data Operators (CDO, Schulzweida 2022). A total of 15 parameters were implemented (Appendix A). In the IAHRIS model distinction was made between 5 categories of river status, with category 1 resembling very good ecological status and category 5 very poor ecological status (table 3).

Table 3: Display of the variety of hydrologic status categories according to the IAHRIS model. Adjusted from Martinez Santa-Maria and Fernandez Yuste (2010a,b)

Hydrological Status *Martinez Santa-Maria and Fernandez Yuste (2010a,b)*					
	Category I	**Category II**	**Category III**	**Category IV**	**Category V**
IHA	0.8<IHA≤1	0.6<IHA≤0.8	0.4<IHA≤0.6	0.2<IHA≤0.4	0≤IHA≤0.2

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Table 4: Overview table for a short description of all indicators of hydrologic alteration used in this study. Detailed explanation of the calculation of the parameters can be found in appendix A.

Overview	
Indicator	**Description**
IHA 1	The annual average discharge.
IHA 1b	The average monthly discharge.
IHA 2	The difference between the annual maximum and minimum discharge values.
IHA 4	The difference between the 90th and 10th discharge percentile.
IHA 5	The average of the maximum daily discharge.
IHA 8	The 5th exceedance percentile for discharge, related to floods.
IHA 9	Coefficient of variability for the maximum daily discharge.
IHA 10	Coefficient of variability of the 5th exceedance percentile for discharge.
IHA 12	The amount of days the 5th exceedance percentile is exceeded within a month.
IHA 13	The average of the minimum daily discharge.
IHA 14	The 95th exceedance percentile for discharge, related to drought.
IHA 15	Coefficient of variability for the minimum daily discharge.
IHA 16	Coefficient of variability of the 95th exceedance percentile for discharge.
IHA 18	The amount of days without any flow (Q=0).
IHA 19	The amount of days discharge is lower than the 95th exceedance percentile.

2.4.3 Water Scarcity Indices

While the prior analysis have been conducted on a cell basis, this is not particularly fitting for water scarcity. Water demands might be concentrated within a relatively small region, maybe even a single cell - think of a metropolis like Bucharest. Its water is not sourced only from the cell most of the demand comes from, a larger area needs to be used. A total of 77 subbasins have been created for this purpose, which comprised of a maximum of 30 000 km^2 (figure 4).

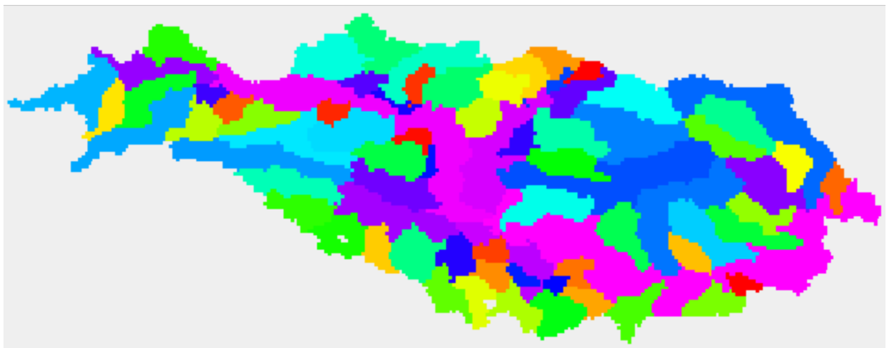

Figure 4: All subbasins created for the computation of the water scarcity.

For this study a broadly used indicator for water scarcity, the Water Exploitation Index Plus (Casadei, Peppoloni, and Pierleoni 2020), was selected. The Water Exploitation Index Plus (WEI+) is a ratio between the consumptive abstractions and the available renewable water resources (see equation 4).

$$WEI+ = \frac{abstractions - return\ flow}{renewable\ water\ resources - environmental\ flow} \qquad Eq. 4$$

In this study an adjusted version of the WEI+ will be used, as the environmental flow is seen as additional competition to the other sectors, furthermore the return flow is not incorporated (Equation 5). While the subtracting the return flow from the abstractions gives a more accurate representation of long-term water availability for a region, the immediate water scarcity is more severe as these return flows are yet to be available. Especially during the summer months in the Danube drought can be a significant problem, and the immediate water scarcity is very important. These circumstances are also the once most severely impacted by EFR inclusion, therefore exclusion of the return flow from the equation is fitting for this study. The EFR is seen as additional water demands – the water is not removed from the river and thus it is still available would emergency arrive, however, we wish to spend this water on environmental wellbeing instead.

$$WSI = \frac{gross\ demand + EFR}{renewable\ water\ resources} \qquad Eq. 5$$

All of these variables are outputs of the PCR-GLOBWB model and can be used directly to calculate the water scarcity. The renewable water resources considered are the inflow coming from upstream, the locally generated runoff and groundwater recharge (Equation 4 and 5). Enforcing an environmental flow will always lead to increased water scarcity, as less water is available for human use. The impact of enforcing an EFR is more severe when renewable water limits are limited.

3. Results

The aim of this study is to apply different EFRs and identify their respective impact on the hydrological behaviour in the Danube river basin. The EFRs, VMF and Q90, have been compared based on a few different characteristics: 1) how much water is reserved and how often is this limit reached, 2) their impact on the WSI and 3) their impact on the Indicators of Hydrologic Alteration. The first section of this chapter will display the historical scenarios. The second section discusses the effect the GCMs have when compared to the WATCH database. The last section regards the future scenarios that use the SSP2 narrative with GCM climate forcing (RCP 6.0). As the GCMs comprise of 5 different runs the figures show an overview of all individual GCMs and an average. Detailed individual figures can be found in Appendix B.

3.1 Historic Situation of the Danube River Basin

3.1.1 Formulation and Implementation of the EFRs

At the basis of this study lies the pristine run. The pristine run shows the hydrologic situation in the Danube River Basin if man-made reservoirs did not exist, no water was abstracted for human needs and without return flows from agriculture or cities. The discharge of the Pristine Run was used to define the VMF and Q90 EFRs. All of the major tributaries of the Danube river catchment are clearly visible. The annual atmospheric balance is achieved by subtracting the evapotranspiration rate from the precipitation rate. The low-lands in Hungary and Romania, the Moldova region and Bulgarian mountains already have a annual atmospheric balance, these regions are vulnerable to droughts (Figure 5B).

The discharge within the Danube is significantly impacted by human activity. As a result of irrigation, industrial and domestic use the water in the main Danube diminishes by up to 800 m^3/s in the Danube delta (figure 5A). Furthermore, there are some relatively dry sections that experience increased flows as a result of return flows. Return flows can originate from waste water or irrigation. These will be of important influence on some of the drought parameters as the low-flow averages are increased by these processes beyond their natural values. Total gross demand can be found in figure 6B, this is important in the final determination of the Q90 EFR size, as the demand allows the value of the Q90 to fluctuate between the soft and the hard limit (section 2.3.1)

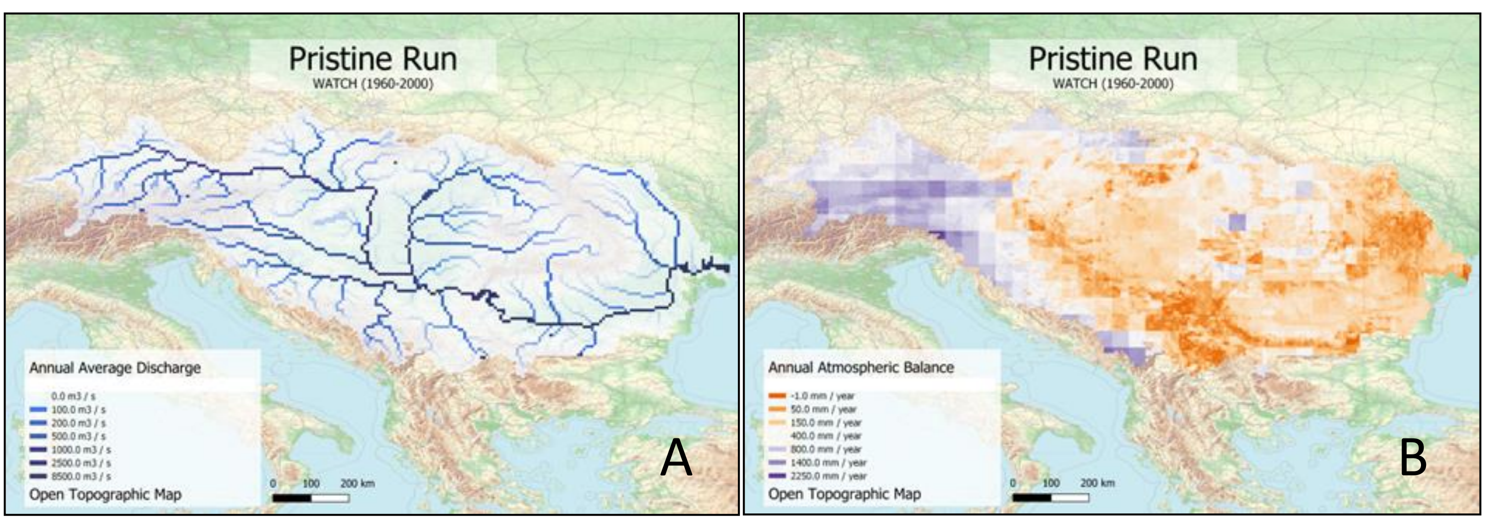

Figure 5: The multi-year annual average discharge (A) and annual average atmospheric balance (B) for the Pristine Run.

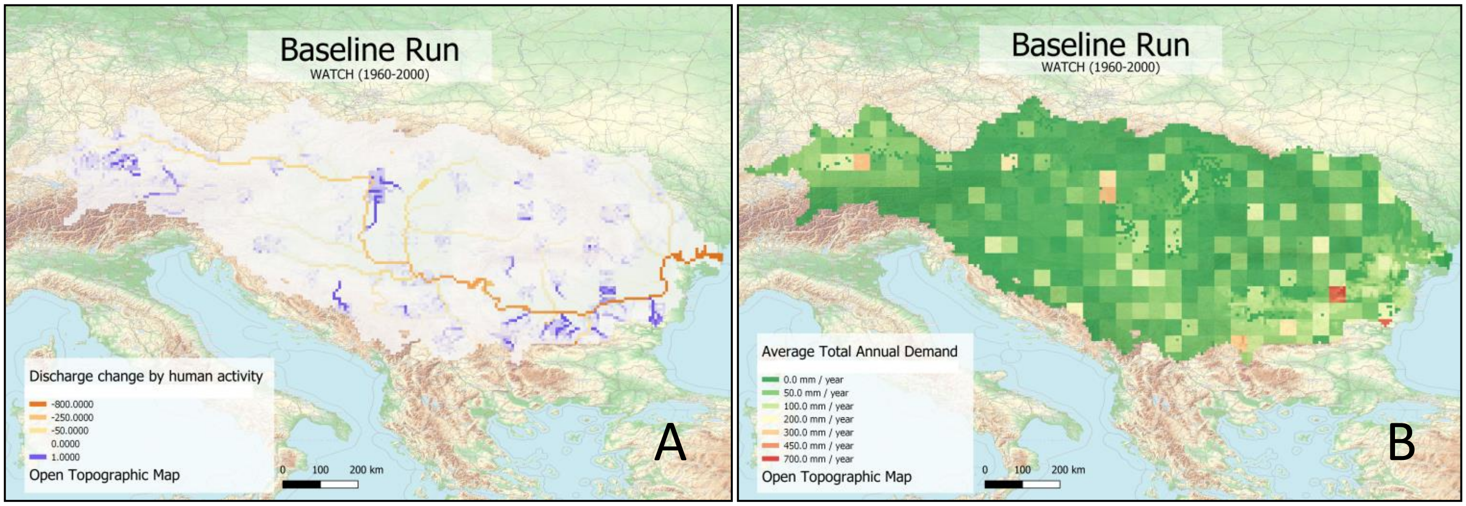

Figure 6: The baseline shows the impact human processes already have on average on the river flow in the Danube catchment (A), the total gross demand (B) is used to set the final value for the Q90 EFR. For the demand there is a more coarse grid visible of 30 arc minutes.

At the core of the Environmental Flow is the amount of water reserved for the environment. As discussed in section 2.3.1, the VMF works with a single hard limit, while the Q90 has a soft limit at its monthly 90th discharge percentile and a hard limit at the annual minimum monthly 90th discharge percentile. In figure 7 the calculated monthly limits for the Danube near Bucharest and Lake Tisza can be seen. The size of demand compared to the availability of water determines the amount of water admitted to the environment. Deviations from the upper 90th percentile limit are caused by relatively large local water demands, this is visible in the Lake Tisza cell. The VMF for downstream rivers generally lower than the 90th percentile method, during dry months the difference decreases or VMF might even surpass the limit of the Q90 EFR. However, for reservoirs and mountainous regions where flow is precarious the VMF has a show larger values. These headwaters have no major inflow from other major streams and are dependent on rainfall in the direct region, while the Danube receives water from many tributaries. Consequently, a drought affecting a tributary can be detrimental to its local environment and population, while the Danube remains largely unaffected.

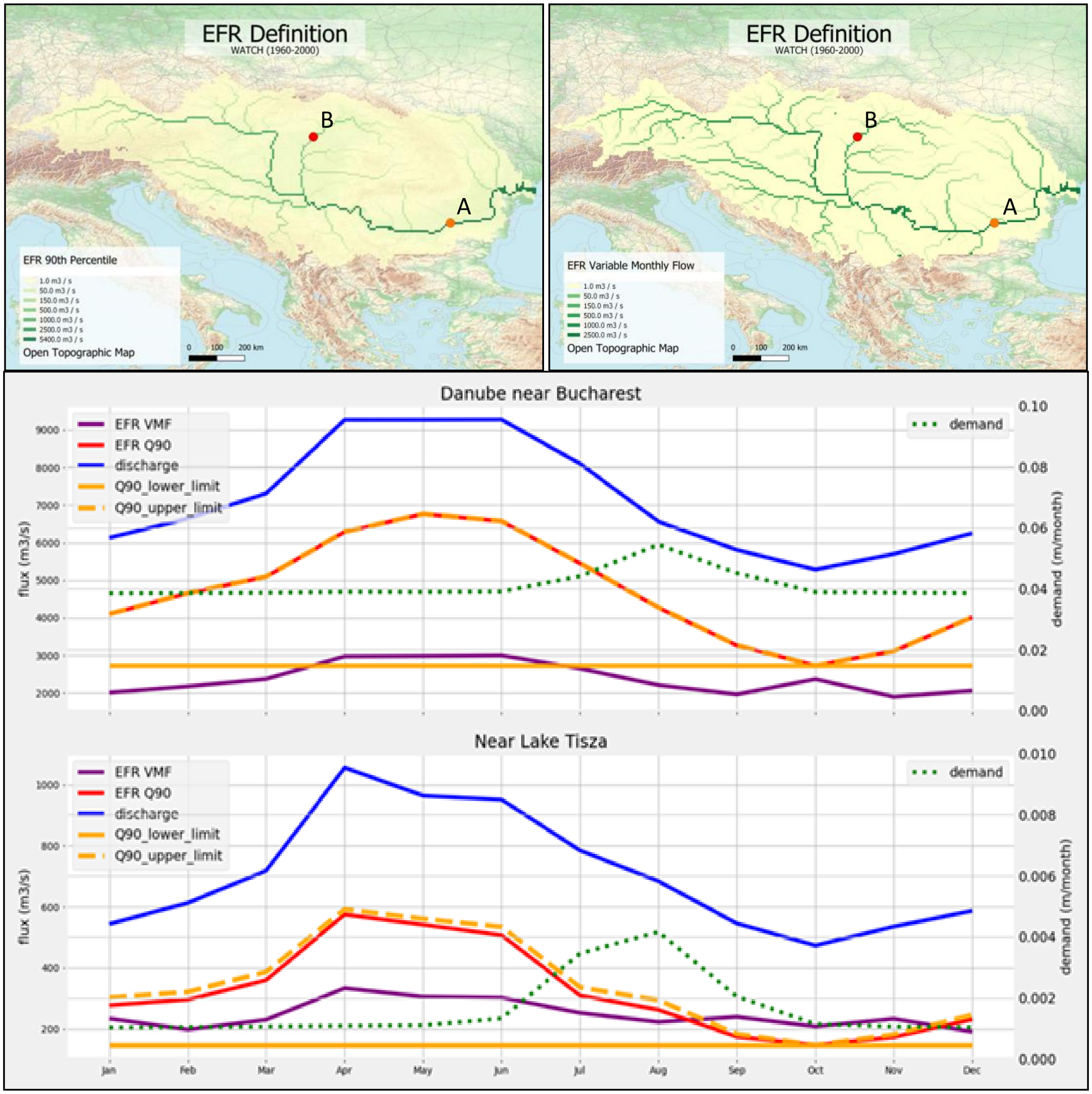

Figure 7: A display of the annual average Q90 EFR (upper left) and VMF EFR (upper right) for the entire catchment. The graphs show the change in EFR throughout the year. EFR changes are set at a temporal resolution of one month. The graphs also show the total gross demand, which determines the exact size of the Q90 EFR. Because the discharge is much lower near lake Tisza (B) the demand has more influence on the EFR than near Bucharest, where even though demand is much higher, this has no relevant effect.

3.1.2 EFR Impact

EFRs will only be of use in times when a low-flow situation occurs, with discharge levels dropping below the EFR limit. Whenever, discharge is high, abstractions are not limited and therefore the situation remains unaffected. In order to determine how much of an impact the EFR might have, determining how often an EFR is exceeded gives an indication of how much effect it might have on the streams flow.

It is important to explain how the EFR Exceedance ratio is calculated, the Q90 might be exceeded more often, although on the average flow reserved might be higher for the VMF. The EFR Exceedance ratio is calculated by checking giving every day within the 40-year period a binary value. If the average discharge of that day is below the EFR, it is valued at one, a higher discharge than EFR is given a zero. The sum of all these days determines the total amount of days during which the EFR was exceeded. Dividing the total sum by the total amount of days within these 40-years gives the EFR Exceedance ratio (Eq. 4).

$$EFR\ Exceedance\ ratio\ (-)\ =\ \frac{\sum_{i=0}^{n} Q_i < EFR_i}{n}$$

With n being the total amount of days, Q being the average daily discharge and EFR being the environmental flow requirement for that particular day. In general, the VMF seems to be in effect more often than the Q90 within the Danube basin (Figure 8B). Only a few streams are blue, and this is at most 0.2 increase, while some cells are exceeded almost continuously with the VMF and almost never by the Q90 (-0.8). Because of the hard limit of 1 m^3/s set for every cell there are many regions where the EFR exceedance ratio is 1. These are areas where no river flows and just rain water falls from time to time.

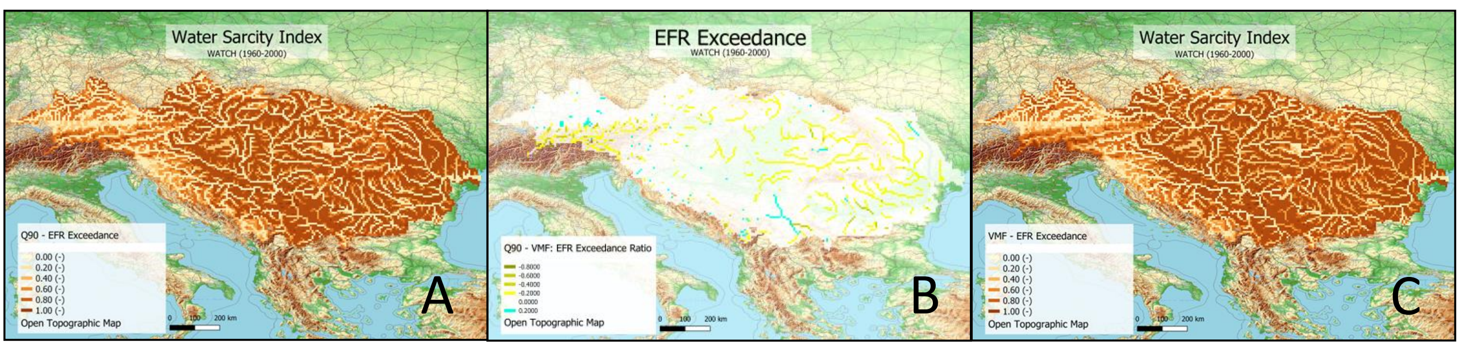

Figure 8: The EFR Exceedance rate for Q90 and VMF, left and right respectively. With their relative difference in the middle (Q90-VMF). The VMF effects streams more often in large parts of the basin, with a few streams being blue, which means the Q90 EFR is exceeded more often.

3.1.3 River Health

The IAHRIS model was adjusted to function with PCR-GLOBWB model outputs and acts as a measure of environmental performance. It was expected that implementation of the EFR would improve the performance of the drought related parameters (Appendix A, IHA 13 – IHA 19). The maximum value for a hydrologic parameter, meaning exact representation of the pristine flow conditions, is one. Therefore, the Baseline scenario performs well, with much of the basin being between 0.9 and 1.0. Areas that have lower performance values are in general more populated or irrigated (figure 9A). It should be noted that all deviations from 1 in this scenario are the complete responsibility of human processes, as this is the only change that occurred between the model runs. Furthermore, the EFRs cannot improve the performance of cells that already have optimal performance for drought parameters.

Because all deviations are by manmade processes, the EFRs have a significant impact, mainly in the Hungarian lowlands. In Romania and Bulgaria the EFRs are less effective, here some of the discrepancies are a result of increased return flows (figure 9A) that decrease the performance of the low-flow parameters. Both EFRs have similar trends (figure 9D), with large parts of the basin being green or red, depicting improvement or deterioration for both respectively. However, these are IHA averages, the drought parameters are the ones that are affected directly by EFR implementation.

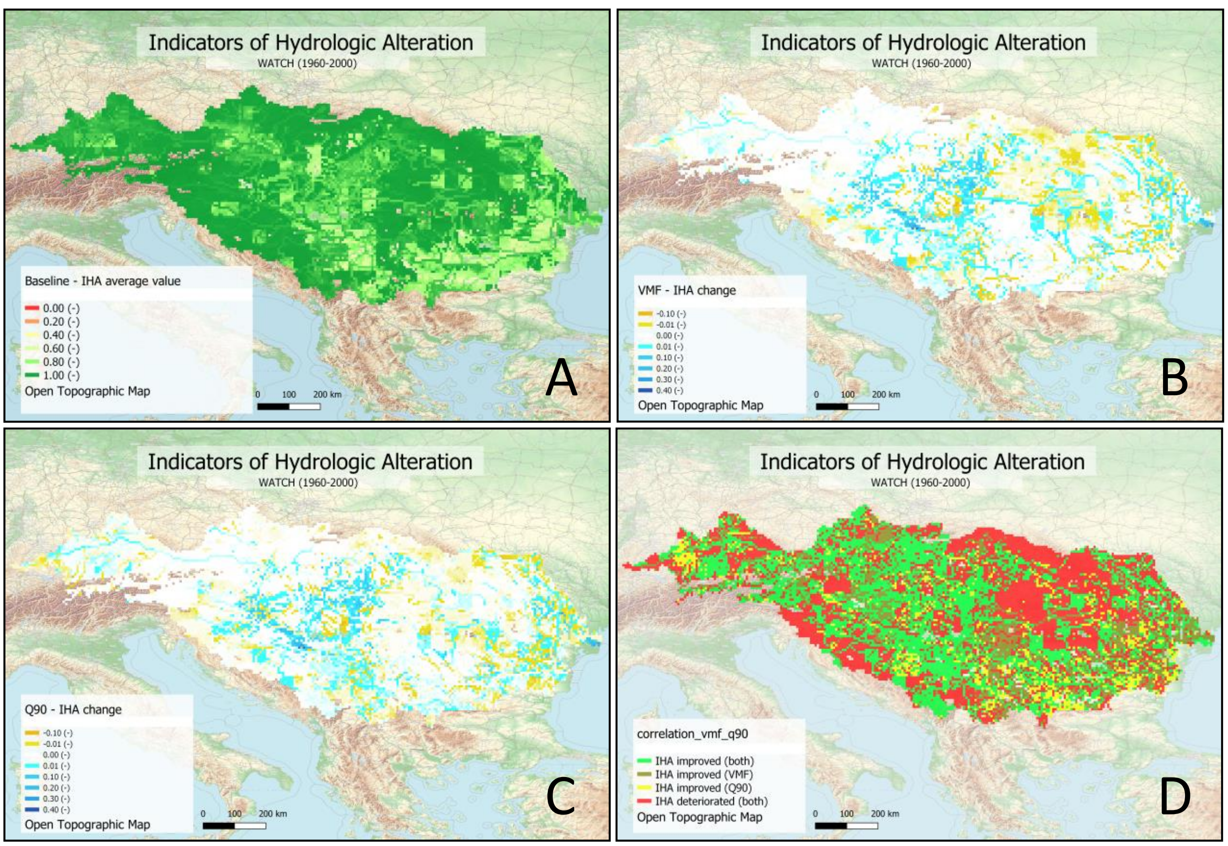

Figure 9: Overview of the A) IHA value during the Business As Usual (BAU) scenario and consecutive change of average IHA values when B) VMF and C) Q90 EFRs are implemented. D) Shows where the IHA average is improved as a result of EFR implementation.

Figure 10B displays the effect of VMF and Q90 EFR implementations on the map average values of the different parameters. It becomes evident that the drought parameters are significantly more affected. Furthermore, the differences between map total and river cells have been analysed, as EFR implementations do only affect rivers as abstractions do not occur in regions where little consistent flow is. A river cell was defined as a cell with an annual average flow above 1 m^3/s. The map average improves more in response to EFR implementation. This mainly originates from the 1 m^3/s global constraint, as a significant amount of non-river cells are consistently protected from withdrawals. The VMF method from Pastor et al. (2014) outperformed the 90th percentile method both for the rivers and the total map averages.

The most pronounced improvement is visible for yearly minimal flow, IAH 13, and the extreme low-flow value (Q95), IAH 14 (figure 10B). Minimal improvements are seen over all parameters except for IAH12 which is based on flood seasonality (see Appendix A). The increase in overall IHA performance is also visible in the range in which most of the cells are situated (figure 10A), with both EFR implementations resulting in a shift towards the right. While the average increase in IHA performance is not great, a clear improvement is visible in the middle of the Danube basin (Figure 9B, C).

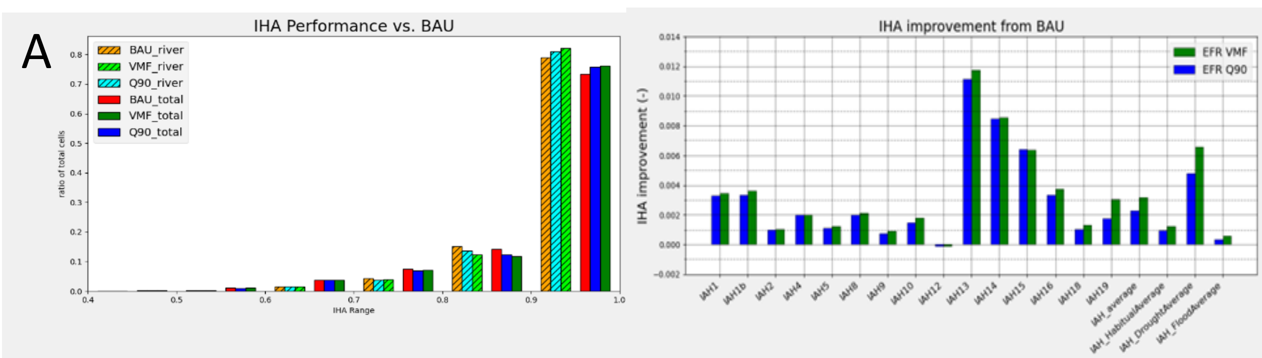

Figure 10: A) Histogram of the IHA performance of each cell as a ratio of the total, with bins of 0.1 in size. As 1 is the maximum value for the IHA parameters, a shift to the left shows improvement. Both environmental flow methods show improvements over the Baseline scenario. B) The change in map average Indicators of Hydrologic Alteration compared to the values to the Baseline scenario. A detailed explanation of the individual parameters can be found in the appendix.

3.1.4 Water Scarcity

Competition over water is more severe in regions where water demand is high or little (renewable) water resources are available. Regions like these are mainly found in the South and Eastern sections of the Danube river basin (figure 11A). Subbasins with heavy industry or large cities also show relatively high WSI values when compared to their direct neighbours, which have similar rates of precipitation. As expected, the implementation of an EFR (VMF or Q90) results in a basin-wide rise on the WSI in response to the additional competition. Effect of EFR inclusion is largest where the EFR itself is relatively large compared to the total amount of water available. The 90th percentile EFR has the highest EFR values (figure 7) in the basins surrounding the Danube channel, resulting in the largest increase in WSI (figure 11B). The VMF has relatively more effect in the mountainous regions with little inflow from other subbasins, but increases pressure within most regions at a similar rate. Both the VMF and Q90 result in a WSI > 1 for the South-Eastern part of Serbia, meaning the implementation of an EFR would make it unfeasible to meet all demands with renewable water sources. Finally, there is severe shift to the right in the water scarcity distribution curve (Figure 11D). This means both VMF and Q90 result in more frequent and severe periods of water scarcity. From figure 11D it also becomes clear that Q90 has a larger impact on the WSI.

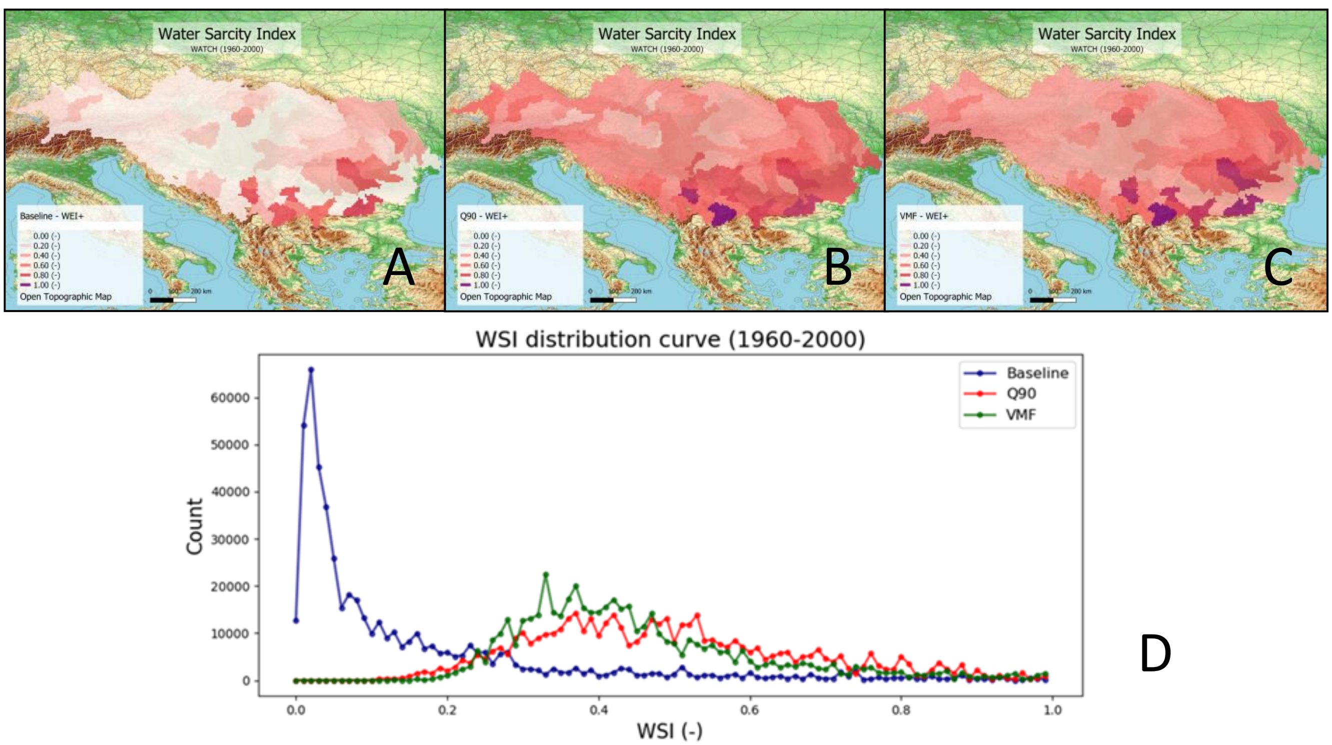

Figure 11: Overview of the WSI in the Danube river basin. The 'average' water scarcity for a basin has been computed for the different scenarios: A) Historic situation without an EFR, Implementation of the VMF (B) and implementation of the Q90 EFR (C). D) shows the water scarcity distribution curve, the EFRs have a very large impact on the water scarcity.

3.2 Comparison of datasets: WATCH vs GCMs

A comparative study of the GCM results for the historic period (1960-2000) and the WATCH was performed in order to understand the faults that come with the use of climate models. While the GCMs have been corrected to closely resemble the WATCH dataset in both its average and standard deviation, there are some clear discrepancies (figure 12). Figure 12 displays the average discrepancy of the GCMs for the EFR Exceedance, IHA performance and WSI. The complete overview of these analysis, with maps for the individual GCMs are visible in figure 13. The EFR is exceeded less often when GCMs are used to force the model, this trend is seen throughout most of the basin, but is especially pronounced near the alps and rivers of NE Romania. The HadGEM model resembles the situation displayed by the Baseline scenario significantly better than the other models, namely for the IHA parameters, with IPSL also showing above average performance. Overall the WSI is similar, a slight decrease can be seen in the South and Eastern sections of the basin except for the subbasin with the main Danube channel. IHA performance diminishes throughout the basin with the largest impact in remote dry regions, and the least for rivers and irrigated lowlands of Romania. These alterations induced by the change in hydrologic forcing only, and this shows the dramatic impact mainly on the IHAs.

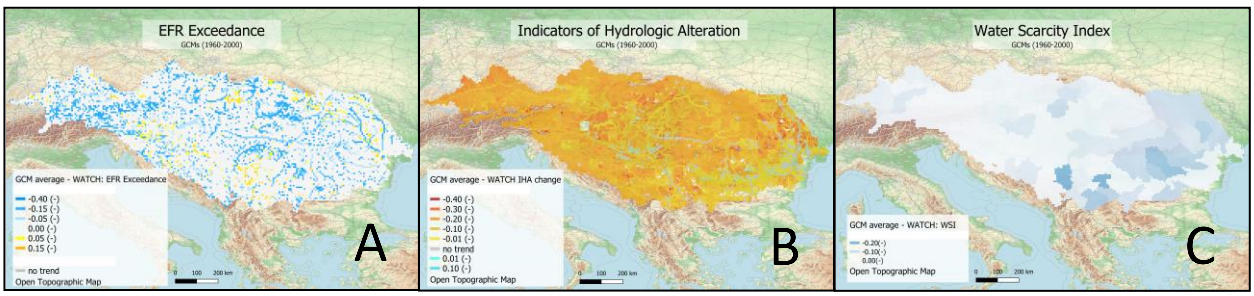

Figure 12: An overview of the difference between parameter values as a result of using Global Circulation Models to force the model instead of using the WATCH dataset. On average there is more consistent precipitation.

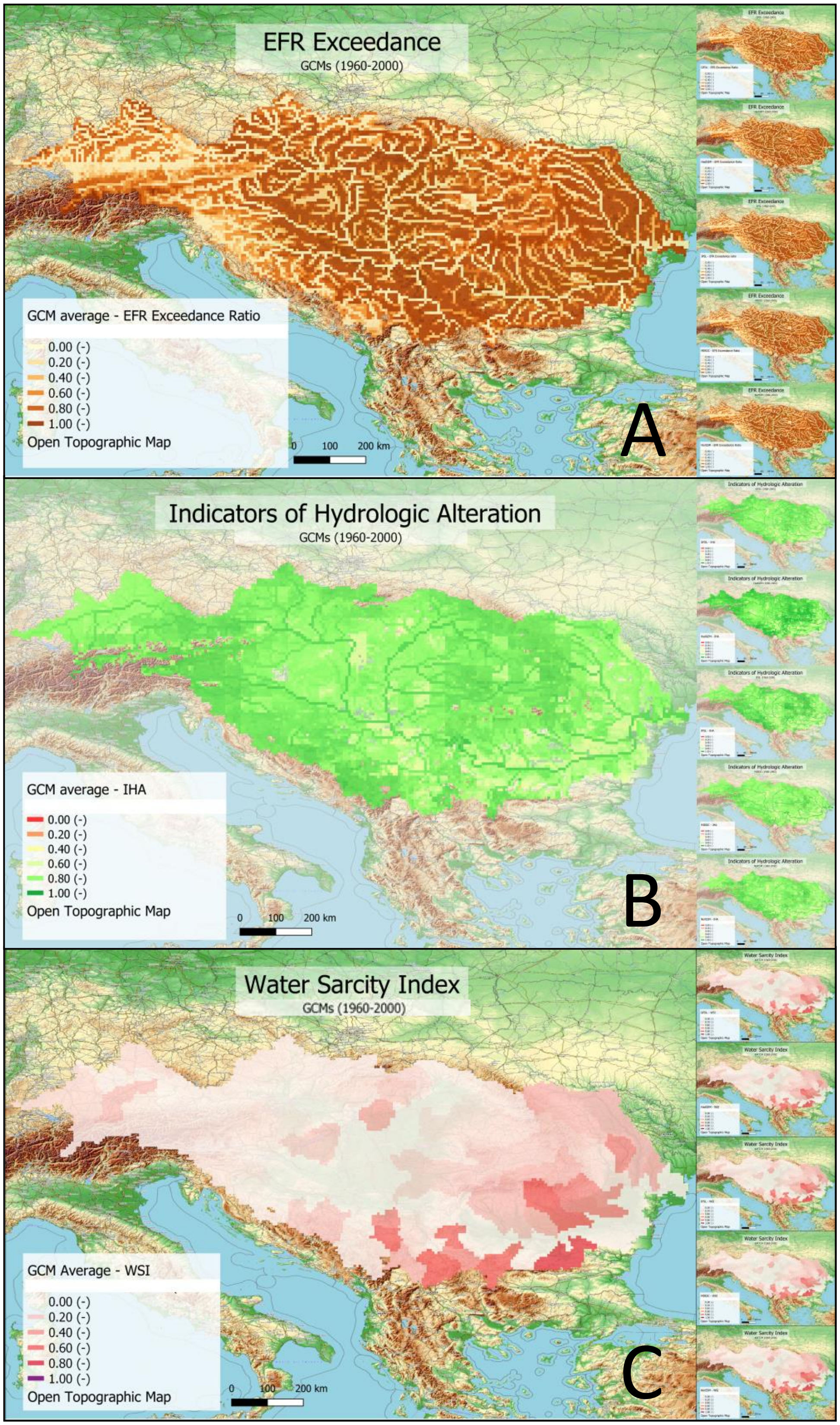

Figure 13: An overview of the average for the GCMs and on the side each individual GCM, from top to bottom respectively: GFDL, HadGEM, IPSL, MIROC, NorESM. For the WSI and EFR Exceedance no immediate differences are apparent, but the IHA is clearly very different for each GCM.

3.3 Future scenarios

In this section we will analyse the changes that occur within the EFR Exceedance, for IHA parameters and the water scarcity during future scenarios. For the GCM average values only trends resembled by all individual GCMs will be shown, other cells will be made grey. Individual GCM maps will be shown on the side and in Appendix B.

3.3.1 EFR Impact

The EFR Exceedance is a key indicator for the effectiveness of EFRs. The historic scenario (1960-2000) served as a baseline, with the early (2010-2050) and late (2060-2100) future showing the change relative to the baseline scenario (figure 14). For the future scenarios the SSP2 socio-economic narrative is used, and therefore water demand and return flows will be different for each time period. The EFR exceedance seems to diminish in large parts of the basin during the early future scenario (figure 15A). Decreases in EFR exceedance might originate from increased return flows or increased precipitation rates. This trend changes for the far future scenario, where exceedance ratios seem to increase for most GCMs, in the South and East of the basin, for the far future scenario (figure 15B).

Figure 14:the EFR Exceedance ratio for the average of the GCMs. One of the most significant things to note is the decreased region that always exceed the EFR. Especially in the more mountainous regions this is visible. The sidebar displays the individual GCMs from top to bottom: GFDL, HadGEM, IPSL, MIROC and NorESM.

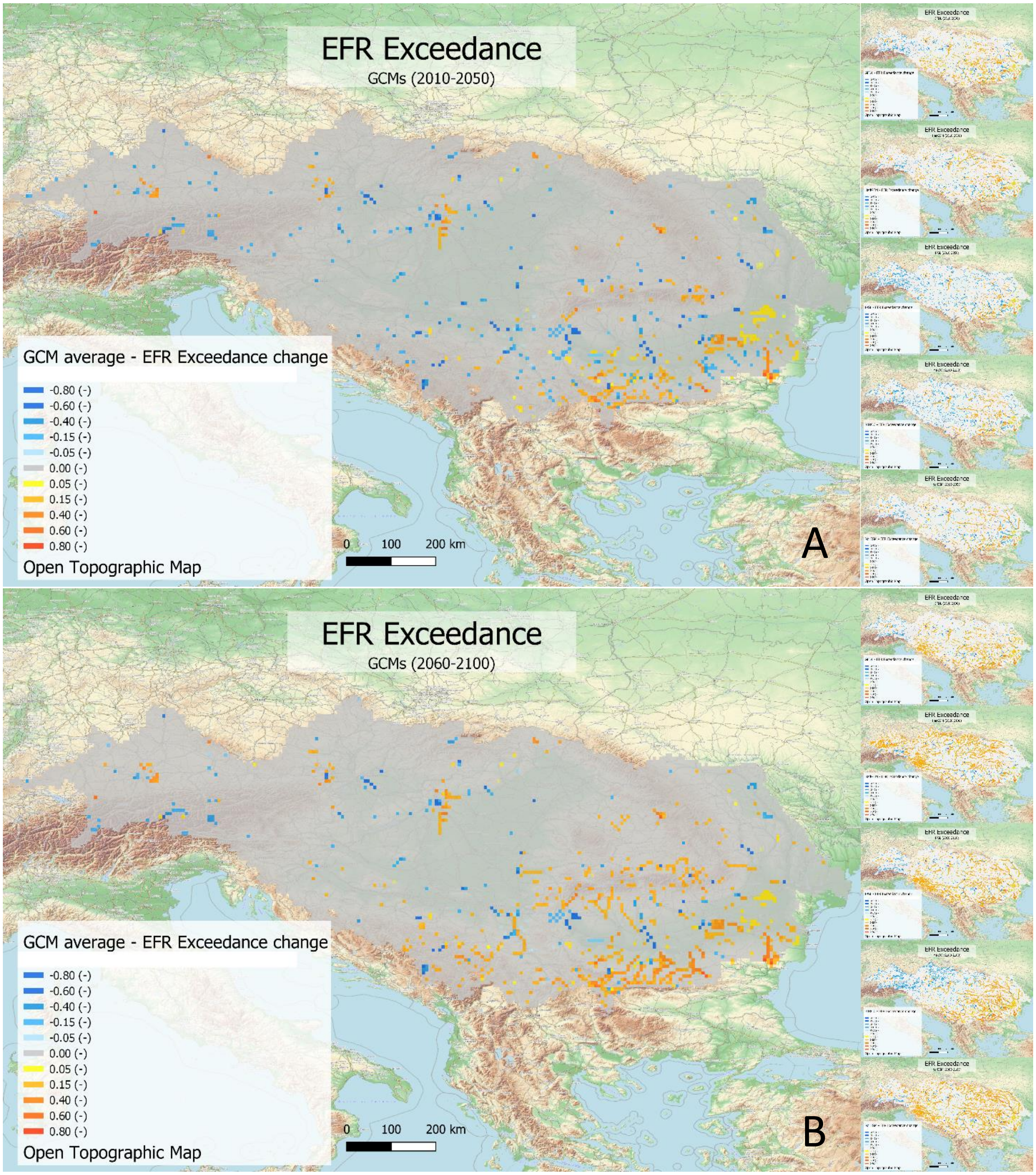

Figure 15: The EFR Exceedance change for 2010-2050 (A) and 2060-2100 (B) compared to 1960-2000 respectively.The side shows the individual GCMs: GFDL, HadGEM, IPSL, MIROC and NorESM from top to bottom. A cell is turned grey if the models do not agree about the trend, the average is shown for cells where all models do agree (all zero or positive . all zero or negative).

3.2.3 River Health

The IHA framework is seen as a measure of the hydrological performance of the natural waterbodies. The IHA performance changes over time in response to changes within the climatology and human demand. However, it becomes evident that climate plays a much more significant role than the EFR, and as such, the influence of the EFR becomes hard to read. Firstly, as the GCMs do not exactly represent the atmospheric forcing data used an IHA average of 1 is not seen (figure 16A). Secondly, implementation of the VMF affects the only drought parameters of the IHA, whereas climatology affects all parameters. Even so, the VMF results in improvements throughout most the basin. The effect is larger in the far future compared to the near future, which partly can be explained by the lower performance in the Business As Usual scenario (figure 16E, 12F).

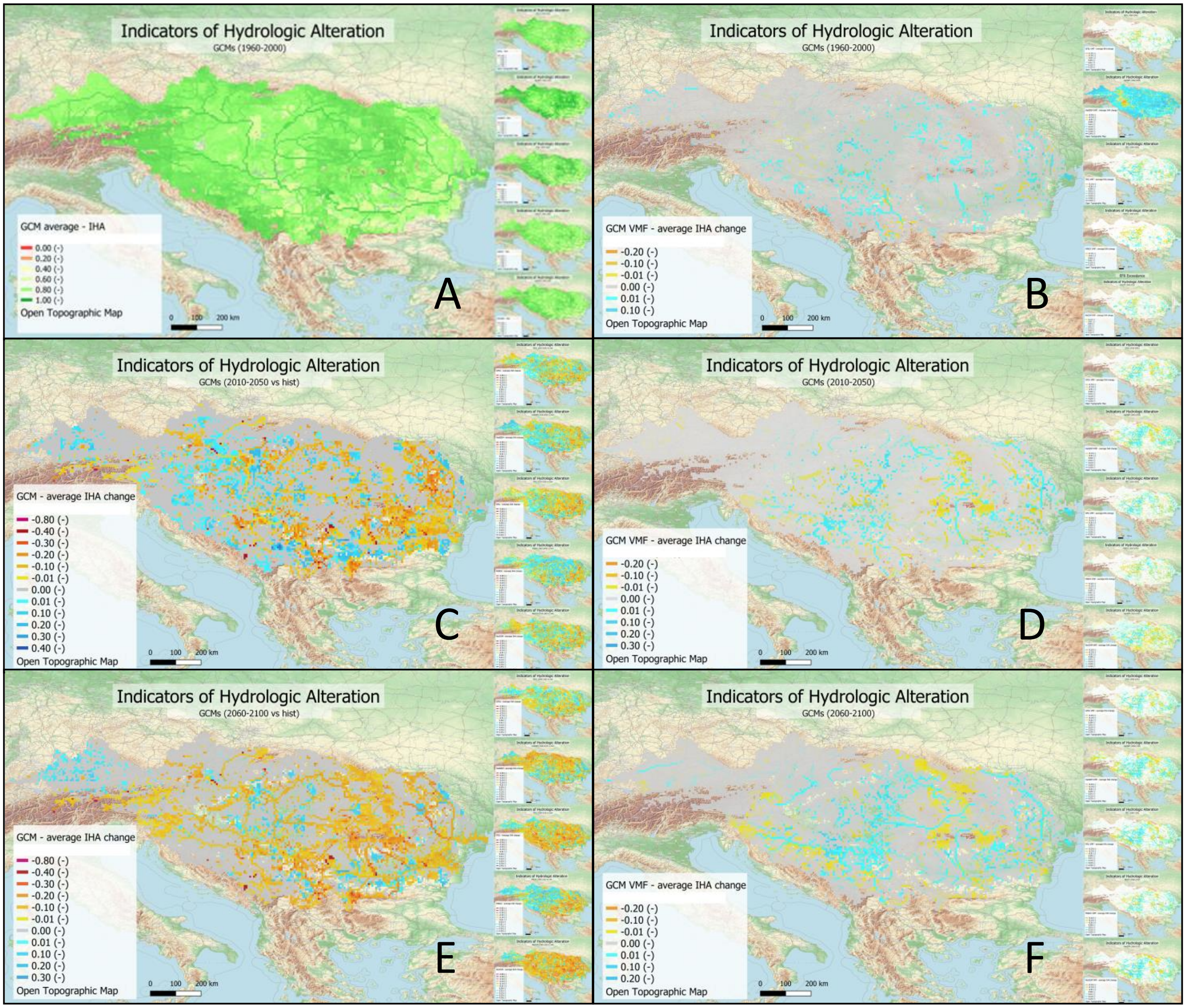

Figure 16: Overview of the average IHA change with time. If there is no trend between the GCMs it was given the color gray - meaning not all GCMs agree on a positive or negative change. The VMF is of relatively low influence in all time periods. The lowlands, which are both well populated and relatively arid, is where river

The IHA serves is used in this study as a measure of well-being for nature. A) As climate models are not able to predict the climatology perfectly: the maximum IHA value is around 0.9, this is in mostly unpopulated area as these are unaffected by humans; Areas affected by human demand (mainly irrigation) show further lowering of the IHA value, around 0.5 around irrigation hubs . As time progresses the climatology changes and changes in human demand result in B) a shift of IHA performance during the near future and than a C) decrease throughout most of the basin in the late future. The effect of the VMF implementation seems to be largest during the historical period, but never exceeds 0.25. On a basin level the average effect is negligible.

This trend of decreased average performance over time can be seen in table 5, the value of individual parameters is displayed in figure 17. VMF has on average a slightly larger impact during the late future. Overall MIROC has the most stable performance and here the VMF decreases the performance of the IHA for the period between 1960-2000 and 2010-2050 for the rivers and the map as a whole. VMF contributes negatively to the drought parameters for the GCM historic scenario, trending upwards to a positive effect in both early and far future scenarios.

Table 5: Overview of the IHA average performance of the entire catchment (A) and rivers (B), which have an average flow above 1 m3/s, for each of the different scenarios.

A	BAU 1980	BAU 2030	BAU 2080	VMF 1980	VMF 2030	VMF 2080
GFDL	0.79	0.77	0.77	0.79	0.77	0.77
HadGEM	0.83	0.78	0.74	0.83	0.79	0.75
IPSL	0.80	0.77	0.74	0.80	0.77	0.77
MIROC	0.77	0.77	0.76	0.77	0.77	0.76
NorESM	0.78	0.76	0.70	0.78	0.78	0.70
Average	0.79	0.77	0.74	0.80	0.77	0.75

B	BAU 1980	BAU 2030	BAU 2080	VMF 1980	VMF 2030	VMF 2080
GFDL	0.82	0.79	0.79	0.82	0.79	0.79
HadGEM	0.86	0.81	0.76	0.87	0.81	0.76
IPSL	0.83	0.79	0.77	0.83	0.79	0.77
MIROC	0.80	0.79	0.78	0.80	0.79	0.79
NorESM	0.81	0.78	0.73	0.81	0.78	0.73
Average	0.82	0.79	0.77	0.83	0.79	0.77

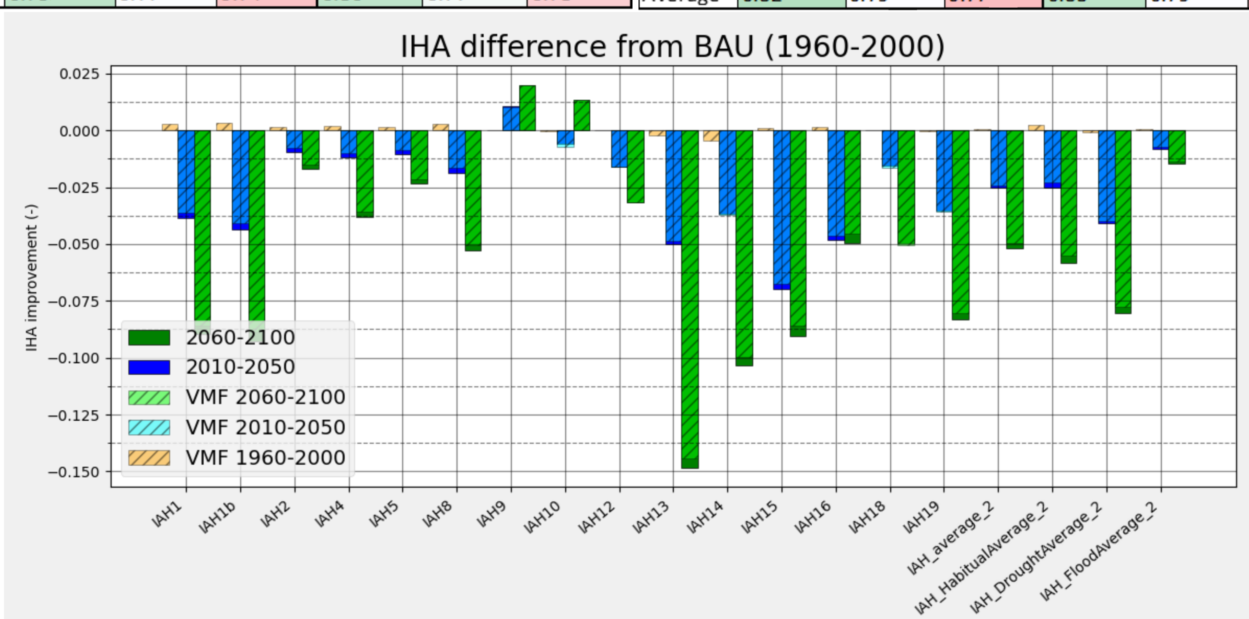

Figure 17: Average performance of the individual Indicators of Hydrologic Alteration. The VMF is supposed to mainly improve the drought parameters (IAH 13 - 19), however, as a result of changes in climate the effect is inconsistent. The IAH 13 (low-flow average) drops when VMF is implemented as there is already a higher average low-flow as a result of the GCM forcing, the VMF enhances this difference.

3.3.3 Water Scarcity

High EFR exceedance seems to be correlated with water scarcity. With the Eastern side of the Danube catchment displaying relatively high values on the WSI (figure 18A). Problems seem to exacerbate in the near future with water scarce regions becoming increasingly more scarce (figure 18B). There are some minor changes in water scarcity between the near and the far future: in Budapest, parts of Bulgaria and Romania there is a decrease in water scarcity, with an increase in Serbia, Austria and the Czech Republic.

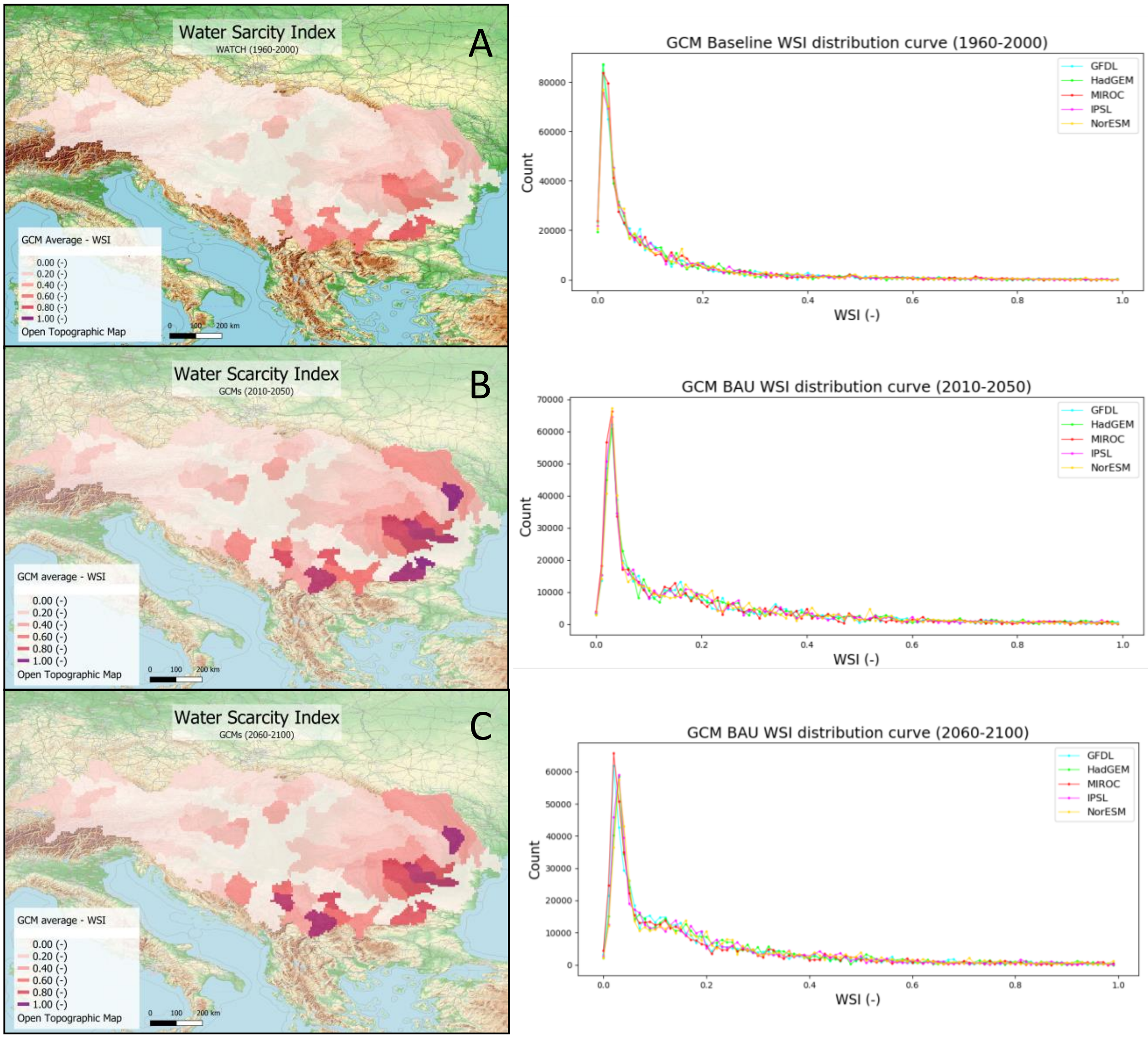

Figure 18: The change in water scarcity distribution over time in the Danube basin. Water scarcity is increasingly gently in both of the future scenarios. The distribution curves for each individual GCM is given on the right side, while the average map gives some idea of what regions are affected by high water scarcity.

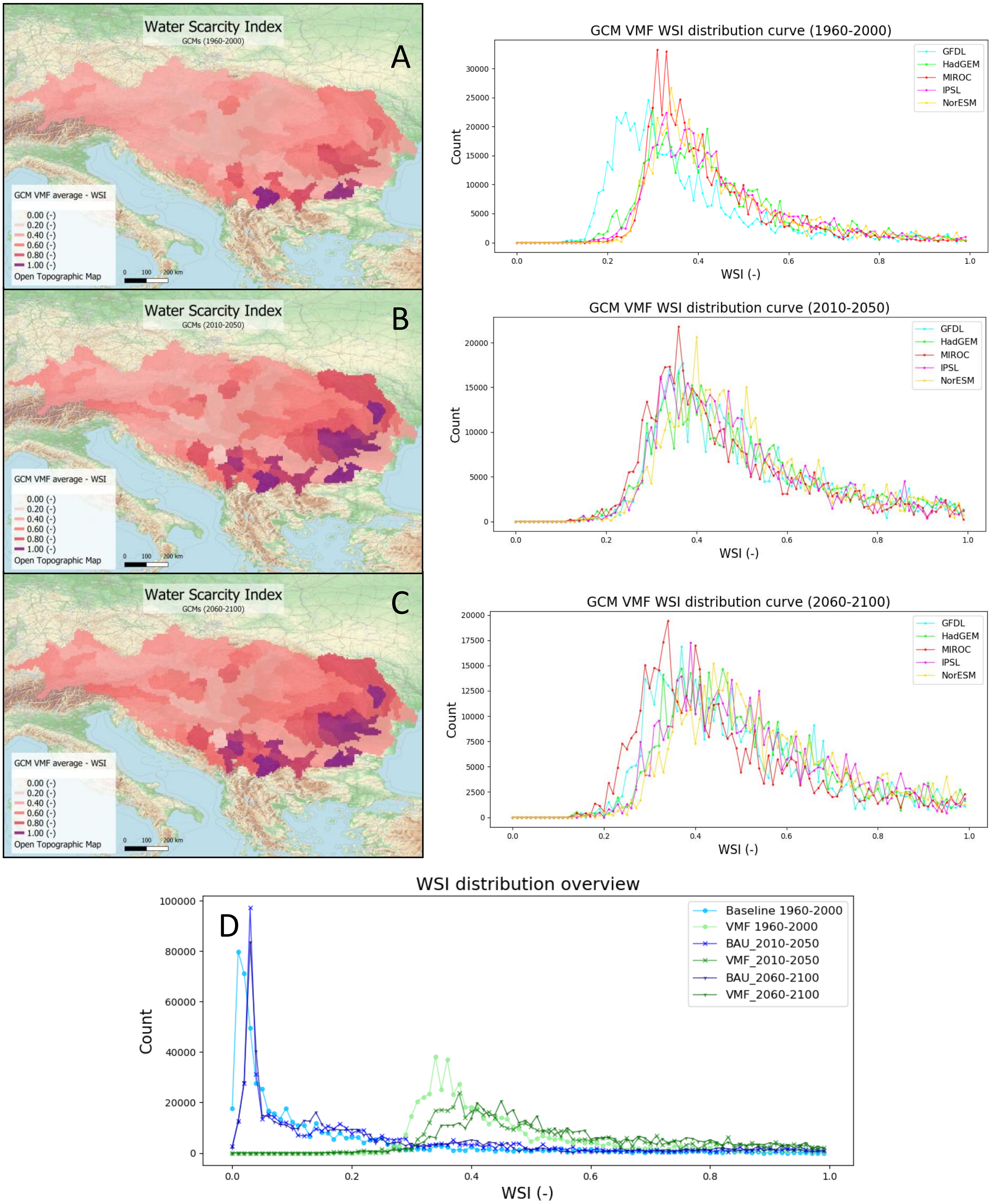

Figure 19: The change in water scarcity distribution over time in the Danube basin with VMF implemented. The trend of increasing water scarcity is now more clear (D), there is a shift in the distribution curves from left to right. The maps function as a way to visualize where water scarcity is most pronounced throughout the year.

4. Discussion

In this study the effect of EFRs on water scarcity and IHAs was investigated through large scale modelling with the PCR-GLOBWB model. Two different EFRs, the 90th discharge percentile and the Variable Monthly Flow (Pastor et al. 2014), were compared to assess the effect of EFR definition on both IHA performance and water scarcity. Subsequently, the best performing EFR was used to analyse its impact in the near and far future. The historical period was use to investigate the discrepancies that existed because of the GCM usage instead of the WATCH database. All scenarios in the Danube river basin were performed at 5-arc min resolution.

4.1 Environmental Flow Requirements and their impact on river flow

EFRs prevent withdrawals when water is below a critical level in order to protect environmental wellbeing (Tharme 2003; Pastor et al. 2014). To establish the impact of the EFR an analysis of the IHAs was performed (Mathews and Richter 2007; Martinez Santa-Maria et al. 2008). IHAs, indicators of hydrologic alteration, are a set of parameters which show the discrepancies between the natural flow and the measured/simulated flow.

We can observe a large quantity of regions improving with the implementation of either EFR during the historic model runs with WATCH forcing data, mainly in the Hungarian lowlands (figure 9). The indicator with the most significant effect in response to the implementation of EFRs in this study was IAH 13, which considers minimal annual flow (see figure 10, table 4). The second largest improvement was for IAH 14, extreme low-flows (Q95). In general the map averages increase only slightly, as a large amount of cells still unaffected by the EFR. For the EFR to have an effect, river flow has to drop below the EFR as a result of withdrawals related to human demand. Furthermore, by limiting abstractions in one waterway, attention might shift to a different local stream to meet the remaining demand. As a result there are a lot of areas with a slight decrease in IHA performance surrounding IHA improvements – the problems are transported to other areas, not solved.

The VMF protects a larger part of the headwaters (figure 14A), this additional water accumulates downstream. As a result is more effective at improving flow regimes than the Q90. The improvements of the IHAs match the EFR being exceeded less often when the VMF or Q90 EFR is implemented. However, this does not imply that low-flow is unaffected by anthropogenic influence once an EFR is implemented. The streamflow will still be affected by abstractions prior to the limit being reached. Therefore EFRs offer some measure of protection, but the low-flow average (IAH 14) and minimal annual flow (IAH13) can still be in deficit compared to the environmental conditions. Although there are a lot of different influences on the flow regime of a river, individual IHAs are still able to provide insight in characteristic changes resulting from EFR implementation.

Interestingly enough, the Bulgarian mountains and some of the Romanian Carpathians experience significant increased water scarcity while having relatively little effect on the IHA performance. This is most likely because the IHA performance might be decreased as a result of increased return flows (figure 6) – this would make the EFR ineffective.

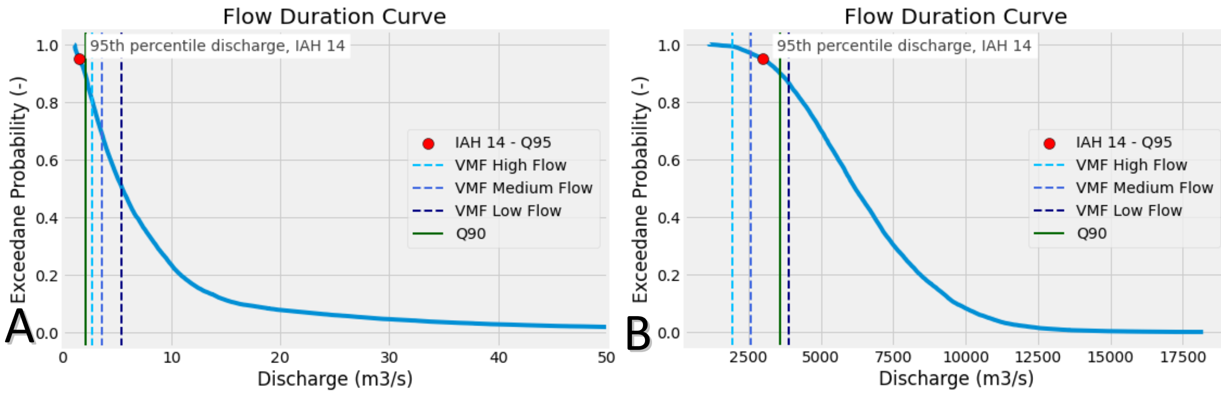

Figure 20: The range at which EFR would protect flow conditions when implemented, and the size of the 95th exceedance percentile. The Q90 EFR should always protect this parameter and VMF most of the time. No additional abstractions would be possible. A) A flow duration curve of a headwater river in the Danube river basin; B) Is the flow duration curve of the main Danube.

While EFR inclusion is paired with improved IHA performance for model runs using WATCH forcing data, when GCM data is used to force the model this trend is seen a lot less. Counterintuitively, the IAH 13 performance, related to average low flow, is worse with the implementation of VMF relative to its Business As Usual counterpart (figure 17).

Similar problems with poor performance of minimal flow indicators when GCM is used to force models have been observed before in scientific research (Shrestha, Peters, and Schnorbus 2014; Kiesel et al. 2019). In one study this lack of performance was explained by uncertainties in the model itself, especially regarding river ice dynamics (Shrestha, Peters, and Schnorbus 2014). River ice is not a prevalent feature in most the Danube basin. Others have remarked the impact of RCP, GCM and ecoregion choice on IHA performance. Certain combinations of RCP and GCM might perform well for one ecoregion, yet none of the combinations performed well for multiple regions (Kiesel et al. 2019).

The fact that this study encompasses multiple ecoregions as well as multiple GCMs has most likely played a significant role in the irregular performance of the IHAs. However, there is clear evidence for overestimated atmospheric conditions being responsible for poor IHA performance. The distribution curve in monthly precipitation values shows zero precipitation, and extremely low precipitation, are heavily underestimated across all GCMs (figure 21). This is detrimental for the parameters most affected by the EFR, the IHA13 and IHA14, as these are both most likely recorded during times of drought. Underestimating the frequency of zero precipitation will lead to an increased average Q95 value. Furthermore, the EFR exceedance rate decreases in many parts in the basin when GCMs are compared to the WATCH (figure 12A). This means in general the EFR will limit abstractions less often, and the only reason for this can be less low flow conditions as a result of different atmospheric fluxes – all other variables have been constant for the historic simulations. The inclusion of an EFR will increase the discharge values as it limits abstractions. If drought parameters are already performing poorly as a result of too wet or consistent conditions this is exacerbated by EFR inclusion. During the near and far future scenarios the frequency of zero precipitation increases, which results in a drop of the Q95 and correspondingly the effect of VMF on IAH 13 becomes positive. As this study has used trends across all GCMs as a method of validation, it would be interesting to see if these changes are statistically significant.

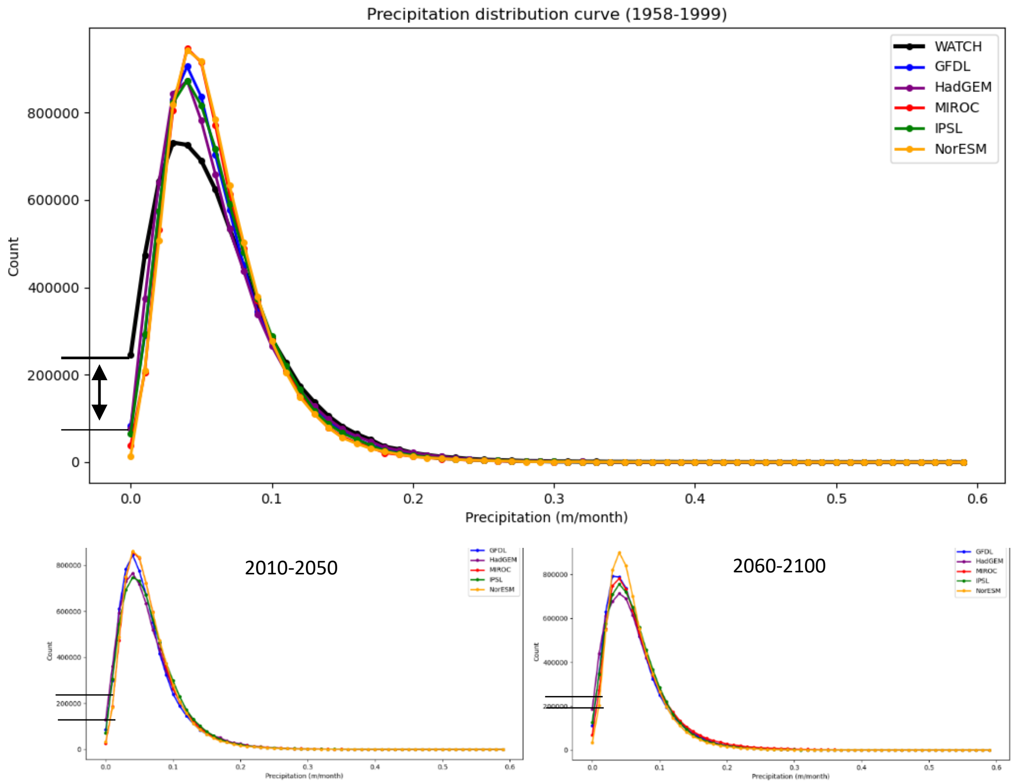

Figure 21: Precipitation distribution curves showing the bias of GCMs which have much less extremely low precipitation values, whereas the WATCH dataset has much more. This difference decreases over time. As there is no data WATCH data for 2010-2050 and 2060-2100 the black line representing the zero precipitation rate for the WATCH is drawn at a consistent height.

4.2 The effect of additional competition over water resources

Increasing the quantity of water available for the natural environment comes at a cost – the amount of competition over water increases. Multiple studies have investigated water scarcity in the Danube river basin with forcing data and socio-economic narratives (Rosenzweig et al. 2004; Barthel et al. 2010; Bisselink, Jacobs, et al. 2018; Bisselink, de Roo, et al. 2018; Mauser et al. 2018; European Commission 2020).

The increased WSI originates from a growing demand for water or a drop in water supply. During the historical Baseline scenario the South and Eastern regions already had the highest WSI values. However, these regions are also expected to experience drought more often during summer in the future (Bisselink, de Roo, et al. 2018). In the early and far future climate change and increased water demand will result in higher WSI values (figure 18). This is in line with prior studies and is explained through increased demand coming from energy generation and population growth in combination with increased periods of drought for the South-Eastern section of the Danube basin (Bisselink, Jacobs, et al. 2018; Bisselink, de Roo, et al. 2018).

By definition an EFR constrains the water availability for humans. As a result the WSI is guaranteed to rise. The 90th percentile EFR and the VMF have distinctly different effects on water scarcity: the Q90 has a large impact on the Danube itself, while headwaters and rivers with irregular flows are affected more by the VMF. Areas with pre-existing problems regarding water scarcity seem to be affected most significantly by enforcing an EFR (figure 19). Shifts in population might decrease the number of people directly effected, however, this is not able to compensate for the additional water demand coming from different sectors. Enforcing VMF during the near and far future would lead to certain regions having a permanent water deficit (figure 19). The number of regions with a permanent water deficit also rise over time, showing the problems exacerbate. Permanent water deficits mean demands cannot be met with renewable water. The change over time is especially well visible for the scenarios with EFR inclusion in the distribution curve. A step wise figure moving over time towards the right is visible (figure 19D). The further the distribution moves towards the right, the more frequent water scarce situations occur.

If water demands are ignored this can result in crop failure, industrial shut-down or lack of drinking water. As the model does not limit groundwater extraction the shortage of surface water in this study is supplemented with groundwater withdrawals. The WSI already incorporates renewable groundwater, therefore regions with a WSI of 1 or higher are dependent on non-renewable groundwater. The size of these non-renewable groundwater withdrawals rises for both the near and far future as less surface water becomes available. In water scarce regions additional groundwater extractions are can go up to 0.08 m/year, which means implementing an EFR could result in a lowering of the groundwater table of up to 7 meters in the time period between 2010-2100. This lowering of the groundwater table will affect basal flow, groundwater recharge and local vegetation. EFR inclusion should therefore be paired with restrictions to groundwater abstraction to have positive long-term effects. Creative ways will have be found to meet the water demands when all these restrictions arise.

4.3 Limitations and Recommendations

It became clear that GCMs underestimated the number of very low precipitation months. As a result the VMF lowered the performance of drought indicators during the historical period. The IHA performance is based on the pristine run, which was based on the WATCH dataset. For future studies it might be more suitable to have a pristine run for every GCM used which will function as natural flow. This will make sure the discrepancies that follow are a result of climate change or socio-economic change, instead of also partly inheriting discrepancies between the datasets themselves. This decrease in performance was the result of an overestimation of the low-flow conditions. Future research regarding the effect of EFRs on low-flows should focus on this parameter, as the other parameters are not directly affected by the implementation of EFRs. Additionally the bias within GCMs regarding low precipitation values should be minimized as these have a drastic effect on minimal flow indicators. As the environmental flow is determined based on the historical period and does not adjust to natural changes in climate, maintaining the EFR might become increasingly impossible.

The research in this paper inherits the limitations of the PCR-GLOBWB 2 model (Sutanudjaja et al. 2018; Hoch et al. 2022). Most relevant is the workings of allocation cells within PCR-GLOBWB. Allocation cells assign within what boundaries water can be used to meet a cells demands. This could result in a situation where a city cannot access a local waterbody because of an allocation cell boundary. The city would then have to find its water elsewhere and might have to resort to groundwater extractions, which would not have occurred could it have accessed the local water body. Furthermore, the added environmental module has limitations of its own. Environmental flows for reservoirs are determined through the discharge at the outlet, while other waterbodies have an environmental flow determined by water height. It was also not feasible to add an EFR to the groundwater extractions. As a result, it was possible that limitations in surface water withdrawals were compensated by groundwater withdrawals.

A lot of the hydrological parameters from IAHRIS (Martinez Santa-Maria et al. 2008) were incorporated to show a complete picture of the influence of EFR on multiple aspects of riverine flow.

However, as a result the impact of important drought indicators were diminished in some of the figures. While the indicators are individually calculated for the entire region of the Danube River Catchment, for the average a mask has been applied. The mask was based on the annual average flow is used to determine which cells are shown, in this study cells with a annual average flow above 1 m^3/s were considered “river cells”.

5. Conclusion

Simulations with the WATCH forcing data show EFRs are an effective way to combat low-flows that result from over-exploitation of water resources. The VMF and Q90 both show significantly increased IHA performance within the low-lands of Hungary and some rivers in Romania. The restriction of water withdrawals by the EFRs enhances competition over the remaining water resources. If water demands cannot be met and groundwater abstractions are not limited, it can have the undesired effect of increasing non-renewable groundwater exploitation. On average the VMF has more of a positive impact on the hydrologic parameters when compared to Q90. Furthermore, the Q90 results in more water scarcity than the VMF, making the VMF the better fit for the Danube catchment. Side by side evaluation of EFR definitions is important to determine the best fit for a catchment.

While the scenarios based on GCM forcing data did not provide consistent results, some trends are still clear. The impact of the EFRs improves over time, as it becomes more effective when droughts occur more severely and/or frequently. Furthermore, the limited water availability after EFR implementation resulted in an increasing area for water scarcity index values above 1. This means the demands cannot be met by local renewable water, and thus has to come from non-renewable sources.

Before EFRs are implemented a thorough assessment of their impact should be completed. The effectiveness of EFRs is much higher in Hungary than in Bulgaria, even though water scarcity rises significantly in both cases. The formulation of the EFR also impacts both the IHA and the WSI, and should therefore be carefully considered.

6. Models and scripts

The script used to calculate the Indicators of Hydrologic Alteration can be found on my personal GitHub page (https://github.com/StevenHosper/CDO_scripts). Any code relevant to the PCR-GLOBWB model will be made available on the UU-Hydro GitHub page (https://github.com/UU-Hydro/PCR-GLOBWB_model) when deemed ready.

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Appendix A

The Climate Data Operators module was used to calculate each of the Indicators of Hydrologic Alteration. A few of the Hydrologic Parameters of Martinez Santa-Maria (2008) were not incorporated as they were either poorly understood or difficult to implement with the aim of this study (IAH3, IAH6, IAH7, IAH 11, IHA17). A Indicator of Hydrologic Alteration is considered as the following:

$$Indicator\ of\ Hydrologic\ Alteration = \frac{IHA_{altered}}{IHA_{environmental}} \quad if\ IHA_{altered} \leq IHA_{environmental}$$

$$Indicator\ of\ Hydrologic\ Alteration = \frac{IHA_{environmental}}{IHA_{altered}} \quad if\ IHA_{altered} \geq IHA_{environmental}$$

Indicator of Hydrologic Alteration 1 is the annual average discharge. This is calculated by using the Climate Data Operator function ‘timavg’ in combination with ‘yearavg’. This takes the average of each of the yearly averages over the time period.

$$IHA\ 1 = \frac{\sum Q_{annual}}{n}$$

With n being the amount of years in the timeseries and Q_{annual} being the average discharge annually.

Indicator of Hydrologic Alteration 1b is based on the monthly mean discharge. This can result in 12 different indicators or a singular indicator, depending on the choosing of the user. In this study the monthly mean parameters were averaged to get a single Indicator of Hydrologic Alteration, as to equally weigh each of the indicators. This was done with the ‘timavg’ (in case of a singular indicator) and ‘ymonavg’ which takes the multi-year average of a month.

$$IHA\ 1b = \overline{Q_{month}}$$

Indicator of Hydrologic Alteration 2 is based on the annual minimum and maximum. With CDO this is calculated with the ‘yearmax’ and ‘yearmin’ functions. After these have been subtracted the ‘timavg’ is taken.

$$IHA\ 2 = \frac{\sum Q_{max} - Q_{min}}{n}$$

The Q_{max} and Q_{min} are the annual minimum and maximum values, n is the amount of years.

Indicator of Hydrologic Alteration 4 is based on the difference between the daily 10th and 90th exceedance percentile. The ‘yearpctl’ operator requires the daily discharge, the yearly maximum and the yearly minimum. If you have calculated the previous indicators these will all be readily available.

$$IHA\ 4 = \frac{\sum Q_{10} - \ Q_{90}}{n}$$

Q_{90} and Q_{10} represent the 10th exceedance percentile and the 90th exceedance percentile. The low-flow Q_{90} is subtracted from high-flow Q_{10}.

Indicator of Hydrologic Alteration 5 is based on the average of the maximum daily flows. It uses the 'timavg' of the prior calculated annual maximum values.

$$IHA\ 5 = \overline{Q_{\max}}$$

Indicator of Hydrologic Alteration 8 is based on the 5th exceedance percentile, correlating to flood discharge. Combining the 'yearpctl' and 'timavg' functions.

$$IHA\ 8 = \overline{Q_5}$$

Indicator of Hydrologic Alteration 9 is based on the Coefficient of Variability (CV) of the maximum flows (IHA 5) in the selected time period. It uses the standard deviation of the annual maximum series and the mean of the annual maxima.

$$IHA\ 9 = \frac{\sigma\, Q_{max}}{\overline{Q_{\max}}}$$

Indicator of Hydrologic Alteration 10 is based on the Coefficient of Variability (CV) of the 5th exceedance percentile in the selected time period. It uses the standard deviation of the annual 5th percentile series and the mean of the annual 5th percentiles.

$$IHA\ 10 = \frac{\sigma\, Q_5}{\overline{Q_5}}$$

Indicator of Hydrologic Alteration 12 is based on the amount of days that the flood discharge (5th percentile) is exceeded, called the flood seasonality. This can be a single parameter or 12, depending on the given choice. A single parameter results in equal treatment of the indicators.

$$IHA\ 12 = 1 - 0.2 * ABS\ (natural - altered)$$

With natural and altered being the amount of days in the month that the 5th percentile discharge was exceeded. A increase or decrease of 1 day results in a 0.2 decrease in the IHA parameter, with full alteration being reached if this changes by 5 days.

Indicator of Hydrologic Alteration 13 is based on the average of the minimum daily flows. It uses the 'timavg' of the prior calculated annual maximum values.

$$IHA\ 13 = \overline{Q_{\min}}$$

Indicator of Hydrologic Alteration 14 is based on the 95th exceedance percentile, correlating to drought discharge. Combining the 'yearpctl' and 'timavg' functions.

$$IHA\ 14 = \overline{Q_{95}}$$

Indicator of Hydrologic Alteration 15 is based on the Coefficient of Variability (CV) of the minimum flows (IHA 13) in the selected time period. It uses the standard deviation of the annual minimum series and the mean of the annual minima.

$$IHA\ 15 = \frac{\sigma\, Q_{min}}{\overline{Q_{\min}}}$$

Indicator of Hydrologic Alteration 16 is based on the Coefficient of Variability (CV) of the 95th exceedance percentile in the selected time period. It uses the standard deviation of the annual 95th percentile series and the mean of the annual 95th percentiles.

$$IHA\ 16 = \frac{\sigma\, Q_{95}}{\overline{Q_{95}}}$$

Indicator of Hydrologic Alteration 18 is based on the amount of days that there is no flow (Q = 0) in a month. This can be a single parameter or 12, depending on the given choice. A single parameter results in equal treatment of the indicators.

$$IHA\ 18 = 1 - 0.2 * ABS\ (natural - altered)$$

With natural and altered being the amount of days that there is zero flow in the natural and altered regime respectively. One additional or less day of zero flow results in a 0.2 shift of the IHA.

Indicator of Hydrologic Alteration 19 is based on the amount of days that there is a flow lower than the 95th exceedance percentile in a month. This can be a single parameter or 12, depending on the given choice. A single parameter results in equal treatment of the indicators.

$$IHA\ 19 = 1 - 0.2 * ABS\ (natural - altered)$$

With natural and altered being the amount of days that there is a discharge below the 95th exceedance percentile in the natural and altered regime respectively. One additional or less day of zero flow results in a 0.2 shift of the IHA.

Appendix B

As there are over 100 figures with a size of more than 10 MB each the figures have been put into a zip folder and are available upon request (s.hosper@students.uu.nl).