# COMPARATIVE ASSESSMENT OF HYDROLOGIC FUNCTIONS AT LARGE RIVER BASINS AND THEIR RESPONSES TO CLIMATE CHANGE

A Dissertation

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By

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## DECLARATION

Except where specific reference has been made to the works of others the work embodied in this thesis is the result of investigation carried out by the author. No part of this thesis has been submitted or is being concurrently submitted in candidature for any degree at any other institution

Rodrigo Fernandez Reynosa

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Abstract

Hydrological functions summarize the hydrological cycle as collection, storage, and discharge. These functions describe the action of a basin on the water entering its control volume (Black, 1997; Wagener, Sivapalan, Troch, & Woods, 2007) as the collection of water from precipitation through different flowpaths onto different storage components (soil moisture, snow, lakes, etc.), and the final release or discharge as evaporation or runoff. The release function, especially the amount released as runoff, is of utmost importance for water managers, as it indicates the water availability. The storage function can have a pivotal role in mediating the partition of collected water into the different releases; however, this link is rather unclear. The objective of this thesis is twofold: First, it will try to determine the current state of hydrological functions; second, it will try to evaluate the effect of climatic changes on these functions. The function of basins is dependent on many factors, including topography, climate, and geology among many others, which is why this study is based in a comparative approach. A global data set of modeled outputs from the EUWATCH project is used, focusing on the 35 largest river basins in the world. The first objective is pursued following the hypothesis that the temporal patterns of each variable can be indicators of how the hydrologic functions work in a basin. This refers to how water is transferred from precipitation (collection function) into storage (storage function) to evaporation and discharge (release function). To study the temporal pattern of hydrological variables, a measure to quantify the degree of similarity in intra-annual variations is introduced under the term of *recurrence* is defined as the degree to which a monthly hydrological variable returns to the same state in subsequent years. The degree of recurrence in runoff is important not only for the management of water resources but also for the understanding of hydrologic processes, especially in terms of how the variables of precipitation, evaporation, and storage

determine the recurrence in runoff. By analyzing these temporal characteristics, a simple hydrologic classification framework applicable to large basins at global scale is proposed. The overview of recurrence patterns at global grid scale suggested that precipitation is recurrent mainly in the humid tropics, Asian monsoon area, and part of higher latitudes with a moisture source from the tropics due to oceanic currents. Recurrence in evaporation was mainly dependent on the seasonality of energy availability, typically high in the tropics, temperate, and subarctic regions. Recurrence in storage at higher latitudes depends on energy/water balances and snow, while that in runoff is mostly affected by the different combinations of these precipitation, evaporation and runoff. Regarding the basin scale classification, in the humid tropic region, the basins belong to a class with high recurrence in all the variables, while in the subtropical region; many of the river basins have low recurrence. In the temperate region, the energy limited or water limited in summer characterizes the recurrence in storage, but runoff exhibits generally low recurrence due to the low recurrence in precipitation. In the subarctic and arctic regions, the amount of snow also influences the classes; more snow yields higher recurrence in storage and runoff. The proposed framework follows a simple methodology that can aid in grouping river basins with similar characteristics of water, energy, and storage cycles. The framework is applicable at different scales with different data sets to provide useful insights into the understanding of hydrologic regimes based on the classification.

To analyze how the hydrologic functions of river basins are affected by climate change, future runoff projections using a Budyko- type equation with respect to projections by a global hydrological model (GHM) were compared. The comparison is made for the annual mean runoff projections for a future period (2060–-2100) after the Budyko parameter is set based on hydrologic model outputs at a present period (1960–-2000). By carrying out this comparison, it was possible to investigate the performance from the

Budyko equation with respect to the hydrologic model at different climate regions and explore the effects of including a hydrologic-function perspective. According to the comparison, the projections by the two approaches agreed well ($R^2 = 0.983$), in particular in humid tropic region ($R^2 = 0.986$) but with consistent underestimation of future runoff (ME = -0.042) by the Budyko equation. In subarctic region the performance of the Budyko equation was low ($R^2 = 0.599$) due to the overestimation of future runoff (ME = 0.110). The results in the dry and temperate regions also showed some discrepancy ($R^2$ = 0.931 and 0.724) without apparent patterns in the errors. The paper discusses possible reasons for the errors with respect to water and energy seasonality and changes in storage component contributions.

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# 1. Introduction

## 1.1. Background

### *1.1.1. Water and the hydrological cycle*

Water is the most important substance on the planet for maintaining all sorts of life. It is essential for human beings not only for drinking purposes but for other activities ranging from food production, industry and energy generation. With population growth, water demand increases largely and requires adequate quantification of its availability and understanding of its behavior on the planet.

Water covers 70% of the earth's surface and is present in several states across the planet. The hydrological cycle is the conceptualization of different fluxes that move water through different stores throughout the globe. These fluxes are mainly evapotranspiration, condensation, precipitation, and runoff. The different stores of water include the ocean, the earth's subsurface, glaciers and the atmosphere where water is not in usable form for human societies as it is not necessarily fresh drinking water. Freshwater only represents about 0.3% of all the water in the earth, and only a portion of is available in rivers and lakes. As water moves through the hydrological cycle it has large impact on climate through energy exchanges due to its phase changes, and also has impacts on landforms through erosion and sedimentation processes.

### *1.1.2. Climate change*

With the growth of industrial activity during the 20$^{th}$ century an increase in greenhouse gas emissions took place which caused increases in temperatures across the globe. Population and agricultural expansion also generated environmental degradation and deforestation further affecting the atmosphere. Aside from natural causes such as oceanic variability, volcanic activity and solar activity among others, anthropogenic activity has exacerbated climatic change as evidence from IPCC states that since the 1950s there has been unprecedented warming over decades to millennia (Pachauri et al., 2014). Climate change further cause changes in atmospheric energy and water components which affect the hydrologic cycle in a direct way.

### *1.1.3. Implications of climate change to the hydrological cycle*

The effects of climate changes in the hydrological cycle are wide, varying at all scales, and include changes in atmospheric moisture content (Seinfeld & Pandis, 2012), precipitation pattern changes (Trenberth, 2011), heavy precipitation over land (Scoccimarro, Gualdi, Zampieri, Bellucci, & Navarra, 2013), and groundwater depletion (Taylor et al., 2013) just to name a few. At the global level, climate change has been affecting processes in tropical cyclone generation (Mendelsohn, Emanuel, Chonabayashi, & Bakkensen, 2012), modification to the El Niño southern oscillation (B. Wang et al., 2013) and changes in monsoonal areas (Turner & Annamalai, 2012).

To water management, the most important indicator of water availability is the water flowing in rivers measured by the discharge and being the result of runoff processes (Schewe et al., 2014). Therefore, the changes in the hydrological cycle that affect runoff are of utmost importance. General changes in runoff include timing and magnitude of spring runoff due to changes in snowfall (Sorg, Bolch, Stoffel, Solomina, & Beniston, 2012), decrease or increase in runoff due to depletion or increase of subsurface water (Taylor et al., 2013; Velicogna, Tong, Zhang, & Kimball, 2012), earlier response of runoff due to urbanization and high intensity rainfall events (Kaspersen, Høegh Ravn, Arnbjerg-Nielsen, Madsen, & Drews, 2015; Kendon et al., 2014), or reduction of runoff due to increased evaporation (Dai, 2013).

In addition to being our indication of water availability, runoff and discharge are also our most direct measurement when it comes to disasters from floods and droughts (Jongman et al., 2014; Mouri et al., 2013). Urban expansion together with changes in heat and precipitation increases the risk of flooding events, landslides, air pollution, water scarcity and drought (Smith, 2013). Rural areas will also experience impacts on water availability and supply, food security and uncertainty in agricultural areas (Pachauri et al., 2014; Qureshi, Hanjra, & Ward, 2013; Wheeler & von Braun, 2013). Some direct implications for water management include the reduction of renewable water availability and growing competition among sectors (Pachauri et al., 2014). Extensive literature has focused on the issue of climate change assessments in water resources seeking to improve our understanding of climate changes on water resources.

#### *1.1.4. Climate change impact assessments*

Since the identification of changes in runoff at the end of the $20^{th}$ century, more and more research has been dedicated to evaluate and project its future conditions (Houghton, 1996; Houghton et al., 2001). Several methodologies have been developed to analyze climate change, all of them under strong scientific background and adding great amount of knowledge; however, they also contain large uncertainties (Bae, Jung, & Lettenmaier, 2011; Deser, Phillips, Bourdette, & Teng, 2012; Heal & Kriström, 2002; Weaver & Zwiers, 2000). One of these methodologies, which was first used as a detection tool, is the statistical analysis of time series (Groisman, Knight, & Karl, 2001; Groisman et al., 2004; Lins & Slack, 1999). With the time series analysis it was possible to detect trends and changes in the statistical stationarity of hydrological variables (Hurrell, 1995; Trenberth, 2011). The time series analysis later was used to project the future conditions of different variables under the assumption that these trends would continue into the future (Boulanger, Martinez, & Segura, 2007). In addition to the simple time series analysis, many studies also involve some stochastic model to implicitly include random processes of hydrology into the projections (Wilks, 1992).

Another concept that has been widely used to identify changes in hydrological variables is the concept of hydrologic sensitivity or elasticity. The concept was introduced by Schaake and Waggoner (1990) as a simple relation between the changes in runoff and the changes in precipitation in the form of the equation:

$$\varepsilon_P = \frac{dQ/Q}{dP/P} = \frac{dQ}{dP}\frac{P}{Q} \tag{1-1}$$

where $\varepsilon_P$ is the elasticity of runoff ($Q$) with respect to precipitation ($P$). This relationship can be applied to other variables also. It can be used in different ways in order to evaluate climate changes. The first way is to evaluate the change in runoff with respect to the change in precipitation with observed or modeled data from historic period (Sankarasubramanian, Vogel, & Limbrunner, 2001). Later, the calculated sensitivity is used to calculate future runoff for any given change in precipitation (Dooge, Bruen, & Parmentier, 1999). The approach may differ if the interannual sensitivity of runoff is calculated in two different periods, analyzing how the runoff response of a basin changes under changed climatic conditions (Liu & McVicar, 2012; Tang & Lettenmaier, 2012). Other variations were later developed as non-parametric estimations (Sankarasubramanian et al., 2001):

$$\varepsilon_P = median\left(\frac{Q_t - \overline{Q}}{P_t - \overline{P}}\frac{\overline{Q}}{\overline{P}}\right) \tag{1-2}$$

where $Q_t$ and $P_t$ are correspondent runoff and precipitation values in a time series and $\overline{Q}$ and $\overline{P}$ are the mean runoff and precipitation values. Recently, more physically based frameworks were developed in an analytical manner (Roderick & Farquhar, 2011), mostly using the water energy framework from Budyko (1974). This framework includes the sensitivity of evaporation and runoff with respect to changes in precipitation, potential evapotranspiration and river basin characteristics.

The third and perhaps most widely used methodology for conducting climate change assessments is through the use of hydrological models (Ghosh & Misra, 2010; He & Hogue, 2012). Hydrological models (HMs) are powerful tools that have been developed in an attempt to represent land surface physical processes (Beven, 2011). Most of the physically based models use widely accepted equations to calculate evaporation and runoff, and use parametrizations to handle water balance in subsurface, surface and snow storage. General circulation models (GCMs) are used to generate global climatic projections which provide the variables that are later used by the HMs to generate future hydrological conditions. Both, GCMs and HMs are improving constantly, providing better representations of climate variables to drive the hydrologic models (Satoh, 2013). Still, there are many parameterizations and equations developed to represent water and energy fluxes and store in the atmosphere and land, creating large uncertainties in future projections (Haddeland et al., 2011; Woldemeskel, Sharma, Sivakumar, & Mehrotra, 2014).

## 1.2. A knowledge gap

Despite all the information and knowledge gathered from the climate change impact assessments, there is still a long road to travel to determine with absolute confidence the future conditions of the hydrological cycle. The usual way to analyze climate change impact has mainly focused on studying runoff changes as a direct result of precipitation changes; however, there is a large amount of information from observations and models that can deepen our understanding. It is important to take holistic approaches that take into account factors such as the storage behavior of basins and how it affects the partition of precipitation into runoff and evaporation. Usually assumptions such as the stationarity of storage are used to simplify our data driven studies hindering our final quantification of water availability. Of course, when using long term projections with hydrological models, the storage within the models readjusts to climate conditions but more attention to this characteristic is necessary.

### *1.2.1. Equilibrium of storage in a changing world*

*Water balance* refers to the mass balance of water in a system, described as a series of inflows, outflows and a mass of water stored that reacts accordingly to these flows. Water balance in a river basin is then described by the following equation.

$$P=E+Q+\Delta S \tag{1-3}$$

where $P$ is the inflow through precipitation, $E$ and $Q$ are the outflows from evaporation and runoff respectively, and $\Delta S$ is the change in storage.

The partition of precipitation into evaporation and runoff is related to the input of energy from radiation that is available to evaporate water. Depending on other factors such as wind and air moisture some of the water will be evaporated and the remnant will become runoff (Penman, 1948; Thornthwaite, 1948). It is usually assumed that the change in storage ($\Delta S$) is equal to zero because $P$, $E$ and $Q$ balance each other. Because the inputs and outputs of precipitation, evaporation and runoff are balanced in the long term, the internal storage of any hydrological system remains in equilibrium, and is assumed constant at large temporal scales. However, it has been identified that at interannual to multiyear scales storage can fluctuate largely in relation to wet or dry years and the storage response further affects runoff (Jothityangkoon & Sivapalan, 2009).

With the alterations of precipitation and the other climatic variables due to global warming, the equilibrium of river basins might be affected. If the change in precipitation and energy compensate each other the basin will remain in equilibrium. However, if only precipitation increases, the equilibrium of the basin could be lost as the storage level would increase further affecting the partition of precipitation. *Figure 1-1* shows the possible hypothetical cases that can result from different changes in precipitation and energy and how storage would accommodate to the new conditions in a schematic manner. These are mere conceptual and schematic representations of hypothetical changes oversimplified used in this document to represent a simplified response in storage. However, the changes in all variables are much more complex. Point *a* in *Figure 1-1* shows neutral conditions where neither precipitation nor potential evaporation increases leaving all conditions same throughout all periods. Point *b* in *Figure 1-1*. shows the case of increasing precipitation while maintaining potential evaporation constant. The increase of the input without an equivalent compensation of outflows would gradually increase storage to higher levels making the basin more saturated. This increase in storage would ultimately result in higher generated runoff. Point *c* in *Figure 1-1* shows the case of increasing potential evaporation while precipitation is kept constant. The increase in water demand in the form of potential evaporation without compensation by precipitation would create larger output through evaporation decreasing the storage level. These conditions would ultimately result in less generated runoff. Additionally, different changes in different seasons can have different impacts in storage and amplify the partition of precipitation towards evaporation or runoff depending on the case.

At small scale (hillslope to watershed scale), there have been extensive studies linking the behavior of storage to runoff generation through different concepts and methodologies (Ali et al., 2013; Bracken et al., 2013; Graham, Woods, & McDonnell, 2010; Sayama, McDonnell, Dhakal, & Sullivan, 2011; Sidle et al., 2000; Tromp‐van Meerveld & McDonnell, 2006) determining the importance that it has regarding residence times (Sayama & McDonnell, 2009) which ultimately influences the sensitivity to climate change (Tague & Peng, 2013). At larger scale several studies have used different approaches to assess the interaction of storage variables and climate using different methodologies. Delworth and Manabe (1988) explored the relations between soil moisture and potential evaporation and how these two interacted and affected climate. Further they explored the relation of the persistence of soil wetness with the persistence of relative humidity by comparing their lagged autocorrelations (Delworth & Manabe, 1989). Also at global scale, the interactions between runoff processes, their feedback with the atmosphere and their effects on simulated water cycle have been thoroughly studied by (Emori, Abe, Numaguti, & Mitsumoto, 1996). Particular to storage components, the effects that precipitation and evaporation have on soil moisture have also been assessed (Huang, van den Dool, & Georgarakos, 1996). Also, the links between trends in precipitation and evaporation with the trends of soil moisture have been analyzed (Hamlet, Mote, Clark, & Lettenmaier, 2007). Macroscale effects of water and energy supplies (Milly & Dunne, 2002) and their influence on river discharge have been also analyzed using observed data and GCMs (Milly & Wetherald, 2002). For river basin characterization with storage information, Masuda et al. (2001) used basin and atmosphere budgets to evaluate water storage and described similarities among storage patterns for major basins in the world. More recently (Kim, Yeh, Oki, & Kanae, 2009) used two indices to quantify the significance of different storage components in terrestrial water storage, namely subsurface storage, snow and river storage, and describe their behavior in 29 basins. Further studies have analyzed macroscale water balance through model simulations assuming that by guaranteeing an accurate streamflow simulation with respect to observations, the simulated evaporation and soil moisture are also accurate

(Maurer, Wood, Adam, Lettenmaier, & Nijssen, 2002). More recently, the climatic responses that drive patterns in soil moisture have been assessed (Georgakakos & Smith, 2001). All these examples have identified that there are important feedbacks between the land surface; however, the link of precipitation to runoff through storage is not yet fully understood in a holistic approach, and how this interactions vary in a variety of climates.

This study attempts to gain understanding of precipitation-storage-evaporation-runoff interaction through a comparative approach that includes basins from all possible regions in the globe. Since the water cycle is highly complex, including many types of processes, an approach which carries large detail is not feasible because each of these processes in itself represents a large diversity of research topics. Instead, the conceptual approach of hydrologic functions (Black, 1997; Wagener et al., 2007) is considered and introduced in the following section.

### *1.2.2. Hydrological functions in river basins*

The hydrologic functions are a conceptualization of the movement of water as it flows through a control volume (Wagener et al., 2007). This a perceptual concept based on the subjective understanding of hydrologic processes, not constrained to the ability to represent the processes in mathematical form (Beven, 2011). At a river basin scale (the whole basin as a control volume) three main functions can be identified (Black, 1997; Wagener et al., 2007):

- *Partition or collection*: The first hydrologic function deals with the input of water to the system. This first function is the collection and partition of precipitation into different flow paths (Wagener et al., 2007) such as infiltration, percolation and throughfall.
- *Storage*: The water from the different flow paths from the partition function eventually reaches different storages like soil moisture, snow, or lake, among

others (Black, 1997; Wagener et al., 2007). The storage function works as a connection between the collection and the release functions.

- *Release*: The last function deals with the output of water from the system. Originally, Black (1997) described it only as discharge, but Wagener et al. (2007) also included evaporation, as it is also a release of water from the system. Depending on the partition function and characteristics of storage, there is the possibility that some portion of water will be partitioned directly into release via direct runoff for example.

These hydrological functions are also dependent and feedback each other. The hydrologic functions are also essential in the conceptualizations of hydrologic models, as the releases from the model are usually functions of the storage volumes.

### *1.2.3. Why a large-scale comparative study?*

The effects of climate change have an impact in the hydrological cycle at all scales (Pachauri et al., 2014). Large scale processes like cyclone formation, and El Nino Southern oscillation, eventually end up having effects at local scales (Stenseth et al., 2002; X. Sun, Thyer, Renard, & Lang, 2014). However, to understand different hydrologic functions it is necessary to compare basins with different characteristics (Berghuijs, Sivapalan, Woods, & Savenije, 2014; Coopersmith, Yaeger, Ye, Cheng, & Sivapalan, 2012). Several countries and regions, such as the United States, Australia, China and Europe have different datasets that allow for basin intercomparisons. Unfortunately, these datasets are only limited to temperate and cold regions, where energy is limited to summer periods and moisture is less prevalent than in tropical regions. Satellite information is readily available with data sets for precipitation, evaporation estimates, and storage change. Additionally, there are several datasets that provide measured data like the Global Precipitation Climatology Centre (GPCC) (Adler et al.,

2003) and the Global Runoff Data Centre (GRDC). EU-WATCH has developed several datasets from reanalysis (Weedon et al., 2010; Weedon et al., 2011) and GCMs (Piani et al., 2010). Within the EU-WATCH project, several modeling groups used the reanalysis and GCM outputs to force hydrological or land surface models to generate a complete data set of water balance (Haddeland et al., 2011; Hagemann et al., 2013). A modeled dataset also has great uncertainties, but EU-WATCH provides results from eight different models which can be used for intercomparison and aid in uncertainty assessment.

The resolution of the data set is at $0.5^{o} \times 0.5^{o}$ or about $50 \times 50$ kms. This resolution prevents a detailed local study, but it allows working with large scale basins. This study included the 35 largest basins in the world, assuring that water balance is closed in each basin. The selection of these basins, assured that all continents (except Antarctica) were considered, both hemispheres were included, different latitudinal regions were taken into account and a wide variety of physical characteristics exist among all the basins. These basins are shown in *Figure 1-2*.

#### *1.2.4. The Top-Down Darwinian approach*

This work uses a now emerging approach in hydrology and other earth sciences referred to as the Darwinian approach (Harman & Troch, 2014) because this study emphasizes a comparative approach and is bound to a large scale study by the resolution of the data. The approach refers to focusing attention on patterns of variations in populations and seeking hypotheses that explain these patterns in terms of the mechanisms and conditions that determine the processes. We undertake this approach by comparing the behaviors of the 35 largest basins to hypothesize about the dominant mechanisms that generate these patterns and their responses to climatic change.

## 1.3. Objectives of this thesis

This thesis attempts to undertake a holistic assessment of water balance to understand the effects of climate change. The main objective is to analyze how the changes in climatic variables will affect the changes in runoff in terms of not only the direct effect but also the mechanistic change that would result from the functional changes due to the storage function readjustment. The study is twofold focusing first on characterizing basins according to similar functions, and later analyzing the change in these functions due to climate change.

To reach the objective of identifying the present hydrologic functionality of basins, the study explores the temporal variations of the four main hydrological variables (precipitation, evaporation, runoff, and storage) under the hypothesis that they can be an indicator of basin functioning. This study assumes that precipitation has a certain temporal pattern; this pattern should transmit to storage as it fills, and then the release in the form of discharge and evaporation should also maintain the same pattern as precipitation. However, different patterns can also exist; some are obvious, like the lags caused by snow, but others involve other factors such as energy/water balances and their timings.

To fulfill the objective of analyzing the effects of climate change on the hydrologic functions, the study conducted a comparison between two methodologies commonly used to project into the future. One methodology is known as the Budyko framework (Budyko, 1974), which is used for relating water and energy balances to describe the partition of precipitation between evaporation and runoff. This framework is supported by extended literature having strong scientific background and mathematical conceptualizations, albeit being a physical simplification that ignores hydrologic functioning. The other framework is the common hydrological model projection, but the analysis pays particular attention to the process changes that come from the storage response to climate change.

To analyze these objectives a global data set is used. This data set was developed by a European Union project called the Water and Change project (EU-WATCH). The EU-WATCH dataset includes climatic forcing data as precipitation and energy variables and hydrological model outputs which allow for a complete water balance assessment. The dataset includes model outputs from the 20$^{th}$ and 21$^{st}$ centuries and permits comparisons from several regions, allowing several responses to be analyzed.

### 1.4. Structure of the thesis

This thesis consists of five chapters as described in the following paragraphs:

Chapter 1 describes the general background of the issues that this study attempts to discuss, and the objectives.

Chapter 2 provides a description of the datasets that are used for this study and gives a description of variables.

Chapter 3 introduces the study to achieve the first objective of analyzing the present hydrological conditions of large river basins by analyzing the temporal characteristics of hydrological variables.

Chapter 4 introduces the study to assess the effect of climate change in the hydrological functions by comparing two approaches to project into the future.

Finally, Chapter 5 concludes by synthesizing the findings of chapters 3 and 4 emphasizing the mechanisms of storage change. The conclusions also provide insight of the policy implications and future directions that can be followed.

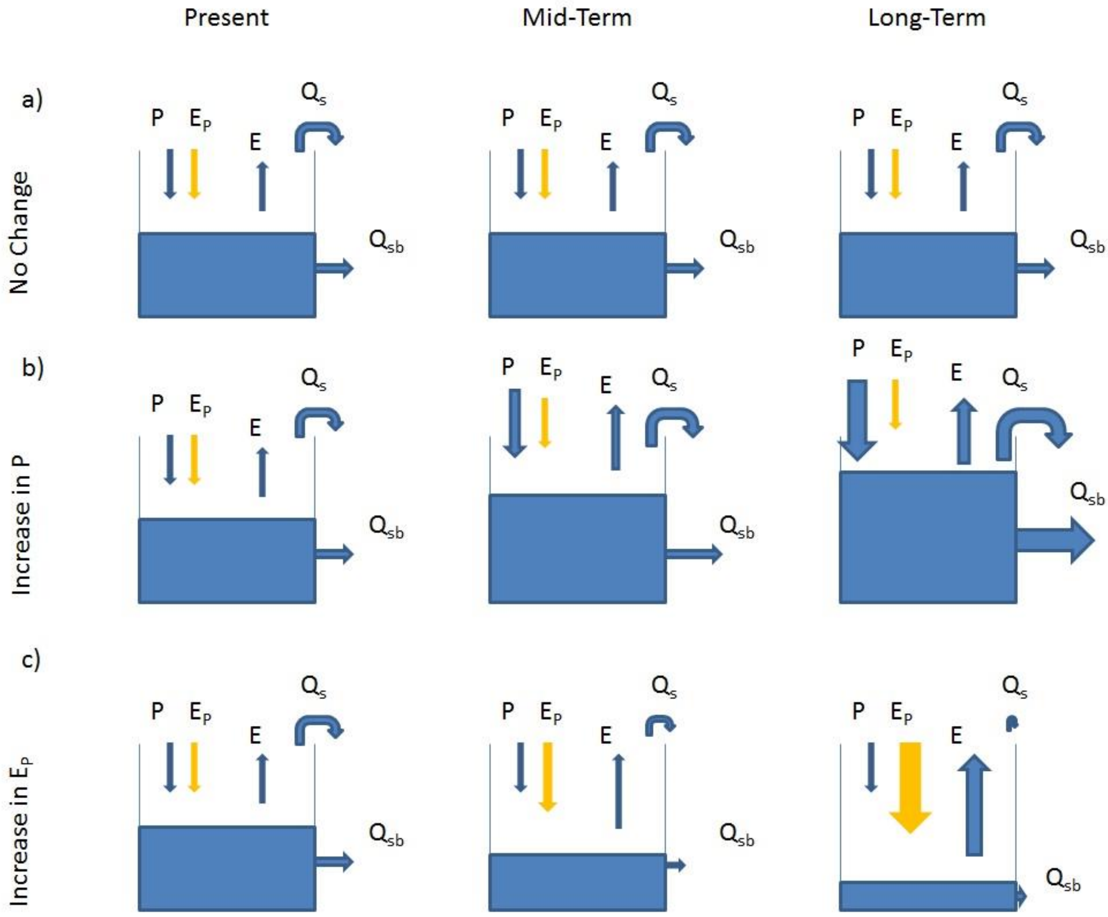


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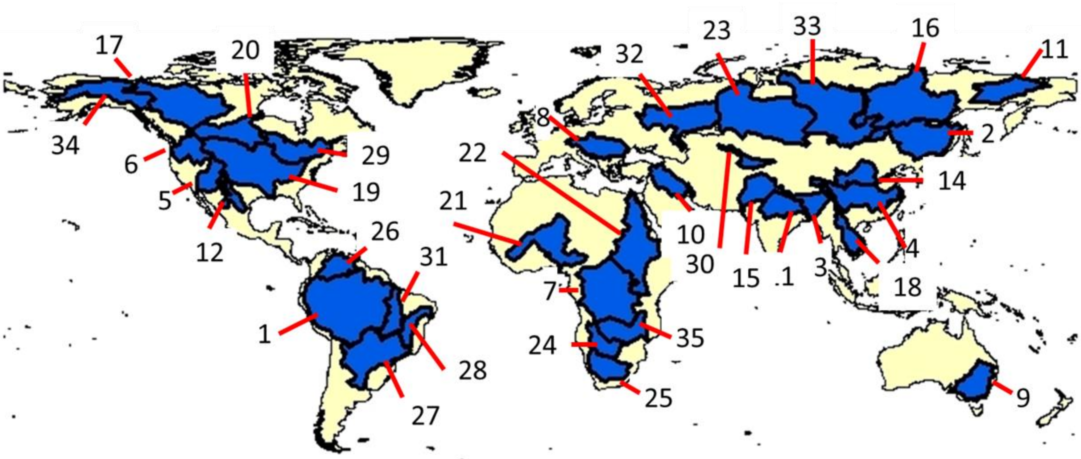
*Figure 1-1.* Conceptual representation of the effects of changes in precipitation or potential evapotranspiration in storage and the further effect it can have in evaporation and runoff: a) no changes, b) increase in precipitation and constant potential evapotranspiration, c) increase in potential evapotranspiration and constant precipitation. $P$ = precipitation, $E_P$ = potential evaporation, $E$ = evaporation, $Q_s$ = surface runoff, and $Q_{sb}$ = subsurface runoff.




| No. | Basin | No. | Basin | No. | Basin | No. | Basin | No. | Basin |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Amazon | 8 | Danube | 15 | Kolyma | 22 | Nile | 29 | Saint Lawrence |
| 2 | Amur | 9 | Darling | 16 | Lena | 23 | Ob | 30 | Syr Darya |
| 3 | Brahmaputra | 10 | Euphrates | 17 | Mackenzie | 24 | Okavango | 31 | Tocantins |
| 4 | Chang Jiang | 11 | Ganges | 18 | Mekong | 25 | Orange | 32 | Volga |
| 5 | Colorado | 12 | Grande | 19 | Mississippi | 26 | Orinoco | 33 | Yenisei |
| 6 | Columbia | 13 | Huang He | 20 | Nelson | 27 | La Plata | 34 | Yukon |
| 7 | Congo | 14 | Indus | 21 | Niger | 28 | Sao Francisco | 35 | Zambezi |

*Figure 1-2.* Basins included in this study.

# 2. Data description

## 2.1. EU-WATCH Overview

The Water and Change project (WATCH) was a project funded by the European Union with the aim of bringing together hydrological, water management and climate communities to analyze, quantify and predict water balance and water resources states. One of the initiatives of the project is the Water Model Intercomparison Project (WaterMIP) (Haddeland et al., 2011). The WaterMIP includes six land surface (LSM) and five global hydrological models (GHMs) which use 20$^{th}$ and 21$^{st}$ century climatological forcing data. The difference between LSMs and GHMs is whether they close energy balance or not. The complete datasets are described and identified in the following sections.

### *2.1.1. 20$^{th}$ century Watch Forcing Dataset (WFD)*

The 20$^{th}$ century Watch Forcing Dataset (WFD) (Weedon et al., 2010) is a meteorological forcing based on a reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-40 (Uppala et al., 2005). The dataset includes variables of snowfall, rainfall, long and short wave radiation, surface air pressure, near surface wind and air humidity. In this thesis, the variables of snowfall and rainfall are aggregated to form total precipitation and the rest of the variables are implicitly taken into account by the hydrological models to calculate potential evapotranspiration and by the land surface models to calculate energy balance. In the rest of the paper we refer to this dataset as the WFD.

### *2.1.2. Watch Driving Data for the 21st century*

The 21st century driving data is also a meteorological dataset developed from GCMs (Piani et al., 2010). The data sets include one control period (1960-2000) and two emission scenarios (A2 and B1) for the 21st century (2001-2100). These scenarios are used by three GCMs to generate the same variables as the WFD dataset to be run in the LSM and GHMs. In the remainder of this paper we refer to this dataset as the WDD. The description of the scenarios and the GCMs is summarized in Table 2-1.

### *2.1.3. Model Output*

The WFD and the WDD are run through six LSM and five GHMs in order to create the land surface components of the hydrological cycle (Haddeland et al., 2011). Each model has different schemes to calculate runoff and evapotranspiration. The different models also contain different storage components which also affect the evaporation and runoff magnitudes. The different parameterizations of storage components, the components themselves and the different equations give quite different results at short scales and different regional representations (e.g. better performance in humid areas than dry areas). For these reasons, general conclusions from global water balance assessments and climate change assessments should not be based on a single model but from a wide range that provide a sense of uncertainty (Haddeland et al., 2011) and therefore this study considers a multimodel database. Due to the availability of the datasets at the time that the data were retrieved, only four LSMs and four GHMs were included in this study. The models are described in Table 2-2. In the remainder of the thesis we will refer to the 20th and 21st Century's Model Output as 20CMO, and 21CMO respectively (Haddeland et al., 2011).

## 2.2. Variable description

To be able to compare the different variables across climates and across models there had to be some treatment to compare the same component within water balance. The definition of each variable is presented as follows:

- *Precipitation (P)*: Precipitation is provided as part of the WFD and WDD datasets. LSMs require input rainfall and snowfall independently provided by the datasets; whereas GHMs use their own algorithms to separate rainfall and snowfall, using total precipitation as input. Since the partitions within the GHMs are not available in the provided EU-WATCH dataset, this study used total precipitation as the aggregated variables of rainfall and snowfall.
- *Potential Evapotranspiration ($E_P$)*: The GHMs calculate potential evapotranspiration with different schemes. Depending on the scheme they selected, they use different climatic variables from the WFD and WDD datasets. The components that each model uses to calculate $E_P$ are presented in Table 2-2.
- *Evapotranspiration (E)*: Each of the models uses different conceptualizations of the land surface as has been mentioned several times. Vegetation, bare soil, surface water, and snow all are treated differently or not included. However, all of the models maintain water balance similarly at long time-scales; hence, total evapotranspiration is the variable provided.
- *Runoff (Q)*: Simulated surface and subsurface runoff for each model are provided independently. However, since the partitions between surface and subsurface differ significantly among models, total runoff is used in this study. River discharge is also provided for some models, but for comparative purposes, total runoff from land surface is selected.
- *Total Storage (S)*: Storage is defined in this study as the total amount of water held in

a basin regardless its physical state or location. Table 2-2 summarizes different storage components aggregated to estimate the total storage in each model. In the discussion of each chapter, further analysis is conducted by using individual components to understand their influence, mostly in contribution to runoff.

- *Ground Moisture (GM)*: Content of moisture percolated into the deep layers of the subsurface isolated from atmospheric effects. This component releases water directly to surface layers. Groundwater storage is a most common term; however, ground moisture is used to keep consistency with the variable definition with the EU-WATCH (EU-WATCH).
- *Soil Moisture (SM):* Soil water content in total soil layer (not independent sublayers), including all phases (vapor, liquid, and ice).
- *Surface Water Storage (SS)*: Total liquid water storage in surface storages like lakes, river channels, reservoirs, and wetlands.
- *Snow Water Equivalent (SWE):* Total water content in snowpack (frozen or liquid).

*Table 2-1.*

*Summary of General Circulation Models (GCMs), and Emission Scenarios Used on These Models.*

**GCMs (Hagemann et al., 2011)**

| Complete Name | Short Name | Center | Description | Reference |
|---|---|---|---|---|
| ECHAM5/MPI-OM | ECHAM | Max Planck Institute | Coupled Atmosphere (ECHAM5) and Ocean (MPI-OM) | (Jungclaus et al., 2006; Roeckner et al., 2003) |
| CNRM-CM3 | CNRM | Centre National de Recherches Meteotologiques | Submodels: Atmosphere: ARPEGUES Ocean: OPA Sea Ice: GELATO 2 | (Déqué, Dreveton, Braun, & Cariolle, 1994; Déqué & Piedelievre, 1995; Madec, Delecluse, Imbard, & Lévy; Royer et al., 2002; Salas-Mélia, 2002) |
| IPSL CM4 | IPSL | L'Institut Pierre-Simon Laplace | Submodels: Atmosphere: LMDZ-4 Ocean: ORCA Sea Ice: LIM | (Fichefet & Maqueda, 1997; Goosse & Fichefet, 1999; Hourdin et al., 2006; Madec et al., 1998) |

**Scenarios**

| Name | World Operation | Population | Economic Development | |
|---|---|---|---|---|
| | | | Scale | Sustainability |
| A2 | Divided | Continuously increasing | Local | Ecologically non-Friendly |
| B1 | Integrated | Rises to 9 billion in 2050 Then decreases | Global | Ecologically Friendly |

Table 2-2.

*Overview of Models Included in This Research and Their Characteristics.*

| Model Name | Precipitation input | Storage components | Provided PET | Reference |
|---|---|---|---|---|
| GWAVA | P | GM, SM, SWE | No | Meigh, McKenzie, and Sene (1999) |
| **H08** | R, S | SM, SWE | Yes | Hanasaki et al. (2008) |
| **HTESSEL** | R, S | SM, SWE | No | Balsamo et al. (2009) |
| **JULES** | R, S | SM, SWE | No | Cox et al. (1999); (Essery, Best, Betts, Cox, & Taylor, 2003) |
| LPJmL | P | GM, SM, SS, SWE | Yes | Bondeau et al. (2007); (Rost et al., 2008) |
| **MATSIRO** | R, S | SM, SWE | No | (Koirala, Yeh, Hirabayashi, Kanae, & Oki, 2014; Takata, Emori, & Watanabe, 2003) |
| MPI-HM | P | SM, SWE | Yes | (Hagemann & Dümenil, 1997; Hagemann & Gates, 2003) |
| WaterGAP | P | GM, SM, SS, SWE | Yes | (Alcamo et al., 2003) |

*Note:* Adapted from (Gudmundsson, Tallaksen, et al., 2012; Gudmundsson, Wagener, Tallaksen, & Engeland, 2012; Haddeland et al., 2011). Model names in bold are considered as LSMs. Precipitation input is either provided as total Precipitation (*P*) or as rainfall (*R*) and snowfall (*S*) separately. Storage can be handled in models as ground moisture (*GM*), soil moisture (*SM*), surface storage (*SS*) and snow water equivalent (*SWE*).

# 3. Understanding the hydrologic functions through a classification of temporal variations of water balance

Parts of the contents of this chapter have been published in Fernandez and Sayama (2015b), including figures and tables.

## 3.1. Introduction

The hydrological cycle, as one of the main earth systems is directly dependent on several periodical cycles with a variety of frequencies. Rotation of the earth on its own axis, rotation around the sun, rotation of the moon around the earth and variations on the earth's axial tilt are the main causes for temporal variations in the land surface and atmosphere. Variations at seasonal scale are the most recognized patterns in most hydrological processes and play important roles in water resource management. Other climatological changes and additional anthropogenic pressure also add to the complexity of the hydrological cycle.

Regardless the complexity, the primary function of a river basin in the hydrological cycle is simply characterized with three main functions: *collection*, *storage* and *discharge* (Black, 1997). The collection function describes the different paths that supplied water from precipitation follows until it reaches a storage component. This collected water is stored at different states and locations within a basin. Water storage, as the first order state variable of river basins, represents its hydrologic condition and serves as the link between collection and discharge regulating the timing and amount of collected water to be released. The discharge function refers to the processes that release the stored water in the form of evaporation back into the atmosphere or as runoff. Among these functions, the prediction and understanding of the release as runoff has been of high importance to understand water hazards and resource management. Nevertheless, as runoff is highly dependent on the other two functions, understanding the dynamics of water collection and storage is unavoidable in order to understand hydrological processes of river basins.

The importance of storage dynamics has been highlighted with emerging new concepts in watershed hydrology. Fill and Spill (Shaw, Vanderkamp, Conly, Pietroniro, & Martz, 2012; Spence & Woo, 2003; Tromp ‐ van Meerveld & McDonnell, 2006), connectivity (McGlynn, Nippgen, Jencso, & Emanuel, 2013, December) and threshold (Ali et al., 2013; C. Fu, Chen, Jiang, & Dong, 2013) are a few examples among various concepts of runoff generation mechanisms highlighting the importance of water storage and its capacity. Recent studies have demonstrated similar concepts at multiple scales based on water balance analysis (Sayama et al., 2011), combinations of soil moisture and streamflow measurements (Sidle et al., 2000), and numerical simulations (Graham & McDonnell, 2010). For larger river basins, there are only a few studies that have identified water storage dynamics at lake/wetland river systems (Spence, 2007; Spence et al., 2010). The stored water volume and its partitioning are important also because they control on residence time and source areas (Sayama & McDonnell, 2009), which ultimately influence on the sensitivity of the system to climate change (Tague & Peng, 2013). Hence storage dynamics should be incorporated as a fundamental metric for catchment classifications and comparisons (McNamara et al., 2011; Wagener et al., 2007).

Jothityangkoon and Sivapalan (2009) introduced a simple theoretical framework for classifying different hydrologic regimes based on storage dynamics on different semi-arid and temperate catchments. The framework shows temporal patterns of storage change with periodic rainfall rate and constant potential evaporation. The amount of runoff generated is assumed to be varied significantly depending on water storage being below or above the soil moisture at field capacity and saturation. Therefore with different balances in rainfall, potential evaporation and the soil properties, other variables including ET, storage and runoff exhibit different temporal patterns, and these are further used for a hydrologic regime classification. The assessment further explores the effects of storminess, seasonality and interannual climate variability and their effect on their proposed regimes. Other examples of different approaches for hydrological classification include (Weiskel et al., 2014) and the series of papers (Cheng et al., 2012; Coopersmith et al., 2012; Yaeger et al., 2012; Ye, Yaeger, Coopersmith, Cheng, & Sivapalan, 2012). Coopersmith et al. (2012) derived the classification using the aridity index, seasonality, and precipitation peak with respect to potential evaporation and the day of peak runoff for 428 catchments in the United States. This classification was further used to categorize hydrological change by analyzing the conditions of the indicators (Coopersmith, Minsker, & Sivapalan, 2014). Berghuijs et al. (2014) used seasonal water balance and temporal interaction of variables to group catchments across the United States.

Larger scales studies have also been done especially for the United States and Europe. Runoff regionalization and classifications have been developed for the Nordic countries although it has been highlighted that further definition of the controls on the identified regimes are still in need (Gottschalk, 1985; Gottschalk, Lundager, Dan, Reijo, & Arne, 1979). In Western and Northern Europe, efforts to regionalize streamflow patterns (Krasovskaia, Arnell, & Gottschalk, 1994) and study the controls of climate, orography and snow in the different patterns (Stanescu & Ungureau, 1997). In the United States, particular to storage components, the effects that precipitation and evaporation have on soil moisture have also been assessed (Huang et al., 1996) even assessing the links between trends in precipitation and evaporation with the trends of soil moisture (Hamlet et al., 2007). Further studies have analyzed macroscale water balance through model simulations assuming that by guaranteeing an accurate streamflow simulation with respect to observations, the simulated evaporation and soil moisture are also accurate (Maurer et al., 2002). More recently, the climatic responses that drive patterns in soil moisture have been assessed (Georgakakos & Smith, 2001).

For global scale, several studies have also assessed the interaction of storage variables by using global circulation models. Delworth and Manabe (1988) explored the relationship between soil moisture and potential evaporation and how these two interacted and affected climate. Further, they explored the relationship of the persistence of soil wetness with the persistence of relative humidity by comparing their lagged autocorrelations (Delworth & Manabe, 1989). Also, at global scale, the interactions between runoff processes, their feedback with the atmosphere and their effects on simulated water cycle have been thoroughly studied by Emori et al. (1996). Macroscale effects of water and energy supplies (Milly & Dunne, 2002) and their influence on river discharge have been also analyzed using observed data and GCMs (Milly & Wetherald, 2002). For river basin characterization with storage information, (Masuda, Hashimoto, Matsuyama, & Oki, 2001) used basin and atmosphere budgets to evaluate water storage and described similarities among storage patterns for major basins in the world. McMahon, Vogel, Peel, and Pegram (2007) did an assessment on the streamflow characteristics for large rivers across the world analyzing their statistical variability and distributions, and later assessed the characteristics in reservoirs (McMahon, Vogel, Pegram, Peel, & Etkin, 2007) and finally intercompared across countries and climates (McMahon, Peel, Vogel, & Pegram, 2007). More recently Kim et al. (2009) used two indices to quantify the significance of different storage components in terrestrial water storage, namely subsurface storage, snow and river storage, and describe their behavior in 29 basins.

These examples ranging from hillslope to global scale have identified that there are important feedbacks and controls between storage and flux components in the land surface and atmosphere; however, the link of precipitation to runoff through storage is not yet fully understood in a holistic approach. How this interactions vary across regions and which are the main drivers for these controls are also not been fully understood. Understanding the dominant controls of basin structure and climate on the hydrologic functions (Wagener et al., 2007) an unifying theories of different controls in different regions (McMahon, Vogel, Peel, et al., 2007) considering holistic conceptualization, e.g. (Black, 1997), is key for defining current hydrological behavior of large river basins.

The objective of the component presented in this chapter is to propose a classification framework for large river basins employing the temporal patterns in precipitation, evaporation, storage and runoff utilizing a global dataset. The frameworks of (Jothityangkoon & Sivapalan, 2009; Kim et al., 2009; Masuda et al., 2001) are followed, in terms of analyzing the temporal variations of the four main hydrological variables in different climatologies to find similarities and dependencies in runoff generation and variable interactions. The temporal variations are assessed by analyzing the recurrence of different variables. It is expected that the different recurrences found in different hydrological variables will provide a regionalization, identify drivers that determine the different recurrence patterns, and that the characteristics of recurrence can provide an idea of the interannual variability and characteristics of extremes in different basins.

## 3.2. Recurrence: Concepts and its measurement

Among a variety of metrics, this chapter focuses on the temporal variations of hydrological variables. Recurrence is introduced as a metric and defined as the degree to which a monthly hydrological variable returns to the same state in subsequent years. The reason for choosing the recurrence as a metric is practical. The recurrence of runoff ($Q$)

and the other three hydrological variables (*P*, *E*, and *S*) are of high importance from a water management perspective. For example, **Error! Reference source not found.** ompares monthly runoff from two different basins with high and low recurrence characteristics. Although total runoff volume and seasonality are obviously dominant factors for water resource management and therefore, many previous classification studies have focused on metrics to represent them (Weingartner et al., 2013), anthropogenic systems have already adapted to the local hydrological regimes to some extent. Generally, it is more challenging for water managers to handle a random pattern with high fluctuations different from past experiences, such as floods and droughts, happening in unexpected magnitudes in unexpected seasons. The feature of a classification using recurrence is to show which variables are recurrent or non-recurrent and how different combinations of recurrence distribute around the world. The discussion of this chapter works under the assumption that the temporal variations distribute through the hydrological variables depending on the hydrologic functionality of the basins. That means that the pattern of recurrence or non-recurrence propagates through the hydrological cycle or is changed depending on the behavior of the functions.

### *3.2.1. Quantifying recurrence*

This section introduces three metrics for evaluating recurrence. We select three statistical measurements used to calculate periodicity and persistence because of the nature of recurrence. We include autocorrelation (AC), fast Fourier transform intensity (FFT intensity) and Colwell Index of Contingency (Colwell, 1974). In this study, since our interest is the recurrence of monthly variable defined above, we used a period of 12 months for each metric.

Lagged Autocorrelation (AC)

- A serial AC defined as (4) describes the correlation of a time series with time lag k:

$$r_k = \frac{\sum_{i=1}^{N-k}(x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{3-1}$$

where $r_k$ is the AC coefficient for lag $k$, $N$ is the total number of observations, and $\bar{x}$ is the mean. This AC calculation loses intensity as the lag increases dying down to zero as it approaches $N$. The AC can further be calculated in terms of the covariance but this computation is considered as a biased calculation of AC. In order to avoid the biased calculation and still be able to calculate a correlation between partial series with larger lags, this series can be assumed as totally separate series with different mean and variance and the calculations can be computed as simple correlation with the following equation:

$$r_k = \frac{\sum_{i}^{N-k}\left(x_i - \bar{x}_{[i,N-k]}\right)\left(x_{i+k} - \bar{x}_{[i+k,N]}\right)}{\left[\sum_{i}^{N-k}\left(x_i - \bar{x}_{[i,N-k]}\right)^2\right]^{1/2}\left[\sum_{i+k}^{N}\left(x_{i+k} - \bar{x}_{[i+k,N]}\right)^2\right]^{1/2}} \tag{3-2}$$

For the recurrence measure with monthly time series, evaluating the AC of time lag 12 only is insufficient because it would only take into account the recurrence in contiguous years. It is more appropriate to include the AC at other multiples of 12. Given the length of the time series used in this study, we decided to use the mean of AC from time lags 12, 24, 36, 48 and 60.

The results will be dependent also on the temporal resolution (e.g. daily or yearly time series). However in this study we decided to use a monthly resolution and look at yearly cycles because one year is usually a unit at which most of human activities and natural cycles repeat themselves.

Fast Fourier Transforms (FFT)

- Another measure tested in this study is Fast Fourier Transform (FFT) intensity which can identify important periods based on a periodogram. The periodical part of a time series can be described by the following equation:

$$m_\tau = \mu + \sum_{i=1}^{h}\left( A_i \cos\left(\frac{2\pi i\tau}{p}\right) + B_i \sin\left(\frac{2\pi i\tau}{p}\right)\right) \tag{3-3}$$

where $m_\tau$ is the harmonically fitted mean, $\mu$ is the population mean, $A_i$ and $B_i$ are the Fourier coefficients, $p$ is a period (12 for monthly data), and $h$ is the total number of harmonics (usually $p/2$).

The Fourier coefficients are calculated as follows:

$$A_i = \frac{2}{p}\sum_{\tau=1}^{p} \bar{x}_\tau \cos\left(\frac{2\pi i\tau}{p}\right) \tag{3-4}$$

$$B_i = \frac{2}{p}\sum_{\tau=1}^{p} \bar{x}_i \sin\left(\frac{2\pi i\tau}{p}\right) \tag{3-5}$$

The intensity can be calculated from these parameters as follows:

$$I_i = A_i^2 + B_i^2 \tag{3-6}$$

The FFT intensity is important to identify the periodicity at a particular frequency. A peak in the plot of intensity vs. frequency (periodogram) identifies a frequency for which a periodical pattern is found. For most hydrological data a peak at a frequency equivalent to a year exists (i.e., 12 months for monthly data, 52 weeks for weekly, and 365 for daily). If a series follows a pattern similar to a sinusoidal function, the intensity will be higher than a series departing from this pattern. Additionally if a series contains much noise the intensity will also be reduced. Hence, a recurrent pattern shows higher FFT intensity. Since the FFT intensity is sensitive to the amplitude and magnitude we applied a standard normalization.

Colwell's Contingency Index

- Colwell (1974) introduced the indices of constancy and contingency, which together form the index called *predictability*. These indices have been used to analyze physical and biological temporal fluctuations. The index has been used widely in the analysis of flowering trees (Colwell, 1974), variations in river temperature (Vannote & Sweeney, 1980), variations in flow velocity (Riddell & Leggett, 1981), rainfall distribution at a yearly basis (Miller, 1984), periodicity analysis in streamflow or rainfall data (Gan, McMahon, & Finlayson, 1991), classification of flow regimes for environmental flow assessments (Y. Zhang et al., 2012), and description of waterholes in hydrological regimes (Webb, Thoms, & Reid, 2012). Colwell (1974) defined predictability as the measure of the certainty of knowing a state at a given time composed by the sum of two components: *constancy*, which represent how uniform the state of a variable is at different time cycles, and *contingency*, which measures the degree to which state and time are dependent on each other.

Calculation of Colwell's index first requires categorizing the continuous data to prepare a matrix. The columns of the matrix represent time categories and rows represent the states of a phenomenon. In this study, the columns represent different months and the rows represent ranges of standard deviations ($\sigma$) whose ranges are between minus four and plus four, which is equally divided into 16 categories with intervals of $0.5\sigma$.

Now let $N_{ij}$ be the number of times that a variable falls in state $i$ at time step $j$. The sum of all columns for each state $i$ is $X_i$, the sum of all rows for each time step $j$ is $Y_i$, and the total number is $Z$. Then Contingency ($M$) of Colwell's Index is defined as follows:

$$M = \frac{H(X) + H(Y) - H(XY)}{\log s} \qquad (3\text{-}7)$$

where s is the number of rows, $H(X)$, $H(Y)$, and $H(XY)$ are defined as:

$$H(X) = -\sum_j \frac{X_j}{Z} \log \frac{X_j}{Z} \qquad (3\text{-}8)$$

$$H(Y) = -\sum_i \frac{Y_i}{Z} \log \frac{Y_i}{Z} \qquad (3\text{-}9)$$

$$H(XY) = -\sum_i \sum_j \frac{N_{ij}}{Z} \log \frac{Nij}{Z} \qquad (3\text{-}10)$$

Contingency becomes 1 if a variable is at the same state at a particular time step, while the index becomes 0 if the occurrences in different time steps take place at the same state. Contingency will be higher as more occurrences in a particular time happen in a particular state. If the values of a variable in a given month are similar, they will fall under the same state interval. This will be the case with variables with high recurrence. For reference, the Constancy ($C$) and Predictability ($P_{red}$) are defined as follows:

$$C = 1 - \frac{H(Y)}{\log s} \qquad (3\text{-}11)$$

$$P_{red} = 1 - \frac{H(XY) - H(X)}{\log s} \tag{3-12}$$

### *3.2.2. Distribution of recurrence and classification*

The variables considered in this study are precipitation *P*, evaporation *E*, runoff *Q* and storage *S*, which compose the general hydrological cycle and are the main components of the water balance equation. *P* comes from the WFD dataset and the rest of the variables come from the 20CMO dataset, all selected at a monthly time step for the period 1979-2001. At global scale or basin scale, each of the four variables are identified as being of high or low recurrence based on the description in previous sections. The first order division of the classification is whether runoff has high or low recurrence, followed by precipitation, evaporation and storage. As a graphical guidance we introduce a classification tree in *Figure 3-2*. The figure shows the 16 possible classes and combinations that were found not within the basins included in this study. It is provided to be used as a guide to understand further figures. We used runoff as the first variable for the classification, as it is the main concern for water resource management, and the other three variables were further used to explain why the runoff in each basin or region shows high or low recurrence. The value used for classifying the basins as high or low recurrence was an AC of 0.75.

First, we quantified recurrence at the global scale, except for Greenland, where the models' performance is questionable due to its particular conditions, and Antarctica, which the EU-WATCH product did not cover. This global analysis was performed for the given time series of each variables at each individual grid. The analysis for the world's largest 35 basins was performed for the time series of each variable considering the spatial average of the grids included within the limits of the basin.

Among all the model outputs from EU-WATCH, particular attention was paid to the WaterGAP model results because it is the only model that includes a calibration module and is closest to observations (Haddeland et al., 2011). Meanwhile, all other model results are also analyzed to cover different model behaviors and discuss model uncertainty.

### 3.3. Recurrence around the world

In this section, the results of recurrence based on AC from the WaterGAP model as the representative case are described. WaterGAP is selected here as it is the only model with a simple calibration module and has better agreement with observations (Haddeland et al., 2011). AC fits our goal because it precisely measures the degree of similarity of each year when lagged by 12 months. Section 3.4 discusses the differences in results for the other metrics and the rest of the different models' results. *Figure 3-3* shows the global distribution maps of the recurrence (i.e., AC in this case) in the four variables: precipitation, evaporation, storage and runoff. From the recurrence calculated for each variable's time series, each grid was identified with red for very low recurrence (<0.5), yellow for low recurrence (0.5~0.75) and green for high recurrence (0.75~1.0). To explain the distribution of the recurrences in the four variables, this paper uses the following terms for different latitude zones for both hemispheres: *Tropical* ($0^o$-$23.5^o$), *Subtropical* ($23.5^o$-$35^o$), *Temperate* ($35^o$-$55^o$) and *Subarctic* and *Arctic* ($55^o$-$90^o$).

The precipitation in the tropical region is basically characterized by the seasonality caused by the oscillation of the intertropical convergence zone (ITCZ) and energy supply due to the effects of the earth's tilt fluctuation. Because of this seasonality, two bands between $5^o$ and $23.5^o$ for both hemispheres show high recurrence in all variables, while they are lower in general at the equatorial band between $5^o$S and $5^o$N where there is no seasonality. The rest of the variables generally follow the same pattern as precipitation although the high recurrence areas of storage and runoff are comparatively smaller than that of precipitation.

The subtropical region is mainly characterized by the latitudinal desert belts. This region is characterized by low humidity and general dryness in soil conditions. In this region, precipitation events are typically sudden and intense without following a certain temporal pattern. During rainfall events, the other variables also behave similarly. Hence, all four variables tend to have low recurrence. The Southeast Asia Monsoon area is an exception due to atmospheric blocking by the Himalayan Ridge which allows warmer temperatures from the humid tropics to reach this latitude, therefore displaying high recurrence in all variables.

The temperate region also shows generally low recurrence in precipitation due to continental climates or oceanic climates with no dry season. Eastern Asia is the only region showing high recurrence due to the effects of the Asian Monsoon. Evaporation in this region has high recurrence due to the seasonality of energy with exception of dry areas in Europe and Asia. Storage has different geographic patterns throughout the region. Runoff follows the same regionalization as storage except for Europe which has comparatively low recurrence in general.

Precipitation in the subarctic and arctic regions shows low recurrence except for some areas in North America and Eastern Siberia. Evaporation also exhibits higher recurrence in this area due to the differential of energy availability from winter to summer. The extent area of high recurrence in storage and runoff is larger in this region, mainly due to the amount of snow.

By taking the spatial average of each variable inside the 35 largest river basins in the world, we calculated recurrence and classified them following the tree illustrated in *Figure 3-2*. *Figure 3-4* shows the result of the classification, which is described below according to each latitude region. *Figure 3-5* graphically displays the results of the calculations of recurrence for each variable. The figure shows the results of the calculated recurrence from the WaterGAP model output and also shows the maximum, minimum, mean and interquartile of recurrence calculated using the other models. Table A1 summarizes the characteristics of each class.

### *3.3.1. Tropical region (0.0$^o$-23.5$^o$)*

The tropical region has the most diversity of classes as seen in *Figure 3-4*. In this region basins belonging to the QPES, QPS, PES, PE and E were found. Mainly, there are two distinct patterns observed in runoff. High recurrence in runoff takes place in the most humid basins exemplified in Point *a* of *Figure 3-6* by Amazon (QPES) and Point *b* of *Figure 3-6* by Orinoco (QPS). Consistent with the global analysis results, we found that precipitation is highly recurrent for these classes due to a repeating pattern resulting from the oscillation of the ITCZ. Evaporation and Storage are also highly recurrent as they follow the same pattern as precipitation as it can be seen in the Amazon time series in Point *a* of *Figure 3-7*. In Point *b* of *Figure 3-6* and Point b of *Figure 3-7* it can also be seen that in Orinoco $E_P$ is much smaller than $P$. This allows for evaporation to increase towards the energy limit at almost any point of the year. The general pattern of $E$ rises and falls similar to the pattern of $P$ following water availability. However, much variability exists as evaporation may rise in dry season reducing recurrence. Storage on the other hand follows the same pattern as precipitation's resulting in a highly recurrent pattern.

More than half of the basins in the tropics exhibit a low recurrence pattern in runoff. These basins are exemplified by Zambezi (PES) and Congo (PE) in *Figure 3-6* and *Figure 3-7*. These basins are drier, with less runoff ratio, than basins with recurrent runoff and they are water limited during some periods of the year. Precipitation shows high recurrence due to the availability of moisture being related to the ITCZ. In these classes evaporation follows the same pattern as precipitation, following the moisture availability pattern. Storage has high recurrence in PES basins mainly because they are characterized by peaks in precipitation and potential evaporation taking place at a different time of the year as seen on the Zambezi River's climatology in *Figure 3-6*. As a result the storage fluctuates largely mainly because the soil moisture component fills in the wet season and nearly dries in the dry season (*Figure 3-6*). This creates a strong seasonal pattern in total storage leading to high recurrence. PE class is characterized by the peaks of potential evaporation and $P$ peaking at the same time (*Figure 3-6d*: Congo PE). Compared to the Amazon, average precipitation is much lower but potential evaporation is almost the same. The Congo basin can be energy limited ($P>E_P$) in the wet season; therefore, regardless of the amount of precipitation, evaporation will reach its potential, creating more recurrent patterns in evaporation. The anomalies in precipitation directly transfer to storage and runoff variations, and since runoff ratio ($Q/P$) and storage change ratio ($\Delta S/P$) are much smaller, these anomalies are larger relative fluctuations to these variables, hence recurrence in storage and runoff patterns is low. The Sao Francisco basin is an exception in this region consisting only of recurrent evaporation. This case is exactly the opposite from the Orinoco-QPS basin and the reason for this behavior is also opposite. Precipitation in Sao Francisco has low recurrence, but it is seasonal, exceeding $E_P$ in the period from November through March season. At this point, regardless of the low recurrence in precipitation evaporation reaches the potential rate consistently year after year maintaining the same pattern. Regarding this difference between Orinoco and Sao Francisco, it is possible that the shape of the basin is an important factor in determining the recurrence of variables. For instance, Sao Francisco is an elongated basin in the North-South direction, whereas Orinoco is not elongated and is located closer to the equator. The variation in moisture availability is larger in Sao Francisco which results in a portion of water limitation, and other portion with a limitation of energy. This condition creates a well-defined repetitive pattern. The constant energy in Orinoco due to its geographical position allows for the pattern explained before.

### *3.3.2. Subtropical region (23.5°-35.0° N/S)*

In the subtropical region, two main classes are observed in *Figure 3-4*. QPES river basins are located in the Southeast Asian Monsoon area, where similar behaviors are observed as the same class river basins in tropical region in *Figure 3-4*. These basins have tropical weather due to atmospheric blocking by the Himalayan Mountain Ridge which prevents colder weather from the north and allows the flow of warmer temperatures from the humid tropics.

On the other hand we can observe the basins that are extremely dry in *Figure 3-4*, represented by Orange basin in *Figure 3-6*. In these basins, all variables follow the patterns of precipitation being, sudden, abrupt and lacking any defined temporal distribution, leading to class L (i.e. all variables have low recurrence). The Indus river basin is an exception in this region belonging to the E class.

### *3.3.3. Temperate region (35.0°-55.0° N/S)*

In the temperate region there are three particular classes observed: PE, ES and E as seen on *Figure 3-4*. All of these classes have low recurrence in runoff and high recurrence in evaporation due to the seasonality in energy supply.

Basins located in Eastern Asia belong to the PE class explained previously on the Tropical Region section. The reasons for this class to be taking place are the same for the temperate region as the tropical region; the reason for recurrence in precipitation comes from the moisture supply following the Asia Monsoon Pattern. Similar to the PE basins in the tropics, these basins have lower *Q/P* ratios increasing the weighing of precipitation anomalies in storage and runoff.

A dominant class in this region is the ES class exemplified by the Mississippi

Basin in *Figure 3-6*. In this type of basin the precipitation pattern is not recurrent without a distinct dry season. Storage is recurrent in these basins as a result of the energy balance characteristics. Due to the limited energy during the winter season, precipitation is directly transferred to storage increase. During the summer, the basins in this class are characterized as being water limited, and therefore, most of the precipitated water is evaporated allowing for storage to decrease. In these basins, there is some influence of snow; however, the amount of snow is not high enough to create a recurrent runoff pattern.

Another group in the temperate region is characterized by recurrence in evaporation only as is exemplified by the Danube river basin. In these basins, precipitation has a pattern of low recurrence that transfers to the variables of storage and runoff. As compared to Mississippi, the Danube River Basin is not energy limited during the summer. This creates a pattern where the anomalies and low recurrence of precipitation also transfer to storage reducing its recurrence.

### *3.3.4. Subarctic and arctic region (55.0$^{o}$-90$^{o}$ N/S)*

In the subarctic region, basins belonging to the QPES, QPE, QES, QE, and E classes were found as seen on *Figure 3-4*. As in the temperate region, evaporation is recurrent due to the seasonality of energy supply. All of the basins in this region, except Kolyma, have recurrent runoff. The runoff pattern is dominated by snowmelt taking place similarly year after year observed in the sudden peak in runoff during spring (*Figure 3-6*h-j).

Basins belonging to the QPES and QPE classes have high recurrence in precipitation due to moisture inflow from the ocean (*Figure 3-4*). The recurrence in storage is dependent on the amount of snow. The climatologies of these basins (*Figure 3-6*, Points h-j) show that storage peaks during the winter months due to the accumulation of snow. *Figure 3-8* shows the climatology of storage in these basins further subdivided into the volume of the different components. Table 3-1 shows the Component Contribution Ratio (CCR), calculated as (Kim et al., 2009) and explained in Appendix A, describing the contribution of each storage variation to the variation of total storage. As it can be seen, in these basins the highest contribution takes place from snow. The WaterGAP model in particular has a small groundwater tank which includes only the dynamical part making it small in volume and contribution. *Figure 3-9* and *Figure 3-10* show the snow water equivalent and seasonal precipitation amounts. From these two figures, we can observe that basins with higher snow amounts have higher recurrence both in storage and runoff.

Basins with low recurrence in precipitation (QES and QE) are basins located on continental areas experiencing precipitation patterns with no defined dry period. From *Figure 3-8, Figure 3-9* and *Figure 3-10* we can also conclude that storage is recurrent for these basins depending on the amount of snow; higher SWE and winter precipitation are linked to higher recurrence. For this region, the recurrence in storage and runoff is independent from the recurrence in precipitation but it is dependent on the precipitation and snow amounts.

## 3.4. The behavior of recurrence and of the classes

### *3.4.1. Characteristics of recurrence measured by AC*

Recurrence vs. seasonality

- This section discusses the characteristics of recurrence measured by AC from monthly variables with the lags of 12 month multiples. Firstly we compare the recurrence and seasonality, following the definition of Walsh and Lawler (1981):

$$SI = \frac{1}{R}\sum_{n=1}^{12}\left|\bar{x}_n - \overline{X}/12\right| \tag{3-13}$$

where $\bar{x}_n$ is the mean of a variable of month $n$ and $\overline{X}$ is the annual mean of a hydrological variable. Hence, the seasonality measures the degree to which each monthly variable of a regime curve deviates from the overall annual mean. Seasonality is essentially different from the recurrence, which, as defined above, measures the degree to which a monthly hydrological variable returns to the same state in subsequent years. *Figure 3-11*displays the relationship between recurrence and seasonality for the time series of each variable from every basin for the WaterGAP model. The figure suggests that generally, higher seasonal variables tend to have higher recurrence. This is because if a variable has strong seasonality, the influence of the deviation from the climatology has comparatively less impact on the AC.

Nevertheless, there are exceptions where variables are highly seasonal but not recurrent. For example, *Figure 3-12* shows the monthly average precipitation in the Ob and Yenisei river basins. The two basins are located in the same latitudinal region, sharing their borders. The climatologies of the precipitation in both basins are similar, with comparable magnitudes at all months. However, the year-to-year variability in both basins is different; Ob shows higher variations than Yenisei. Therefore the precipitation in Ob has lower recurrence (0.65) than that in Yenisei (0.88). Similar cases can be observed when comparing the climatologies shown in *Figure 3-6* and the measure of recurrence presented in *Figure 3-5*, and in previous work, such as Kim et al. (2009) where storage climatologies show strong seasonality but the yearly time series does not behave in a recurrent manner.

To further explain the difference between recurrence and seasonality, *Figure*

*3-13* is presented to show several examples. Case 1 represents a repeating sinusoidal pattern with small amplitude resulting in low seasonality and high recurrence. Case 2, is a randomly generated series without seasonality and low recurrence. Cases 3 and 4 are precipitation of the Yenisei and Ob with similar seasonality, high recurrence in Yenisei, and low recurrence in Ob as discussed above. Case 5 is a sinusoidal pattern repeating the exact same values and shows high seasonality and recurrence. Case 6 adds a decreasing trend to Case 5, but it keeps similar seasonality and recurrence. In summary, seasonality is calculated from the climatology of a variable which results from a long term average, while recurrence measures the year to year variability of the monthly pattern of a variable. Recurrence is an additional feature of temporal patterns of basins, providing different information than seasonality.

*Figure 3-14* shows the distribution of seasonality and recurrence in all variables for the 35 basins with the results of the WaterGAP model. Precipitation shows high recurrence in most of South America, most of Africa, Southeast Asia, and the majority of basins in Eastern Asia (*Figure 1-14* Point *a*). In *Figure 3-14*, Point *b*, seasonality is not that strong for the majority of the basins, aside from a few basins in Africa and the Ganges in Southeast Asia. *Figure 3-14*, Points *c* and *d* show the recurrence and seasonality of evaporation, respectively. Evaporation is the most recurrent variable. However, the seasonality is low except for the subarctic basins related to the availability of energy. This highlights the fact that the pattern of a variable can be repetitive, hence being recurrence, without it necessarily experiencing opposite extremes (seasonality) in a year. Runoff is mostly recurrent in some basins of the subarctic region and some basins in the tropics and Southeast Asia (*Figure 3-14*, Point *e*), whereas it does not display seasonality except for the Ganges and Lena basins (*Figure 3-14*, Point *f*). Finally, Storage is a recurrent variable in some basins of South America, Africa, and Asia, as can be seen from *Figure 3-14*, Point *g*. In the case of storage it does not display significant seasonality around the world

(*Figure 3-14*, Point *h*).

Recurrence vs. aridity

- Recurrence in runoff and storage also has some relation with the aridity of a basin as well as the timings of energy and water availability. These basin characteristics are essential in determining the hydrologic functionality of river basins as they are a descriptor of how much water from precipitation is transferred to evaporation, storage change or runoff and they have been included as classification indices in previous works such as Berghuijs et al. (2014); Coopersmith et al. (2014); Coopersmith et al. (2012); Jothityangkoon and Sivapalan (2009). *Figure 3-15* shows the relations between aridity, timing of peaks in $P$ (water supply) and $E_P$ (energy supply) with recurrence in runoff and precipitation by region.

*Figure 3-15*, Points a and b show that in humid basins, where the runoff ratio and the storage change ratio are high, runoff and storage follow the patterns in precipitation. Drier basins have low recurrence in runoff (classified as PES, PE, ES or E), essentially due to the high sensitivity of runoff to precipitation under smaller runoff ratios. For example, the case of the Amazon and Congo, aforementioned in section 3.1.1, has differences in the recurrence of storage and runoff. For precipitation, both variables have similar relative variations but the total precipitation in the Congo is about 70% of the precipitation in the Amazon. Additionally, the runoff ratio is smaller in the Congo (0.40) than in the Amazon (0.45). The physical meaning of this aspect is that there is less water volume in the Congo transferring from precipitation into storage fluctuation and runoff generation. Hence, the same anomalies in precipitation have a larger impact in the Congo than in the Amazon. Furthermore, recurrence of storage and runoff depend also on the timing of $P$ and $E_P$ peaks. As *Figure 3-15* Points *c* and *d* indicate, the recurrence becomes higher if $P$ and $E_P$ are out of phase (>2 months).

### *3.4.2. Recurrence measured by FFT intensity and Colwell's Contingency compared to AC*

The proposed indices to measure recurrence are lagged AC, FFT intensity and Colwell's Indices. For most of the cases, the basins that show higher AC also have higher values of FFT intensity and Colwell's Predictability. However, it is to be noted that some basins showing lower AC and FFT intensity have high Colwell Predictability, especially in dry conditions. For example, in the arid basins, where all the variables are low in magnitude most of the time except for abrupt peaks, AC and FFT intensity are low, while Colwell's Constancy and Predictability are high. However, these basins are rather low in Colwell's Contingency (Table 3-2). Contingency measures the degree to which state and time are dependent on each other, measuring the degree to which a particular state takes place at a particular time. For this reason, Colwell's Contingency results are highly consistent with the results of AC and FFT intensity. Colwell's Contingency is not only consistent with the other indices but also adequate for measuring recurrence as defined above. Table 3-3 shows the classification of each basin using the different metrics.

*Figure 3-16* shows the correlation between AC and FFT intensity and AC and Colwell's Contingency from the WaterGAP model. All indices correlate well, although there are particular cases that deviate from the regressions. As mentioned in Section 3.2.1, the threshold selected for AC was 0.75. For FFT intensity and Colwell's Contingency measures, thresholds of 150 and 0.25 were selected to minimize the number of basins categorized as different classes.

The FFT procedure is used to represent a time series by fitting a sine and cosine function; therefore, the FFT intensity will be higher for variables following a sinusoidal pattern. *Figure 3-17* exemplifies the different periodograms with their respective partial time series and climatology. *Figure 3-17* shows the example of evaporation in

Changjiang, for which a highly sinusoidal pattern indicates high AC and FFT intensity. It also shows an example of low recurrence with low AC and FFT intensity. However, there are two examples where the FFT intensity value indicates low recurrence while AC indicates high recurrence. First, *Figure 3-17* (evaporation in Congo) shows a bimodal pattern that has a high AC but low FFT intensity; since the peaks in evaporation appear at different frequencies, the intensity at a period of 12 months becomes weaker and other high intensities appear at different frequencies. The second example shown in *Figure 3-17*, takes place with basins in the subarctic region, where the highest volume in runoff comes from snowmelt in early spring but the peak in precipitation takes place during the summer, creating a lump in the recession of the runoff climatology. This second lump reduces the intensity at a period of 12 months and increases other frequencies seen on the periodogram. For both of these cases with deviations from a sinusoidal function, AC better represents the concept of recurrence because if the same pattern repeats, independent of the shape of the pattern, AC at lag multiples of 12 will be higher.

Colwell's Contingency also has high correlation with AC. However, Colwell's Index is mainly used for qualitative descriptions in ecological sciences, but it is adjustable to time series when variable intervals are used as states. Limitations of the use of Colwell's Index for hydrological time series has been extensively discussed by Gan et al. (1991) and include the dependence of the results on the amount of classes selected, and the tendency for higher values in contingency with shorter record lengths. These are the intrinsic limitations of Colwell's Index with the discretization of data.

### *3.4.3. Result dependency on model structure*

Model differences and uncertainties have been widely discussed in literature about model intercomparison (Haddeland et al., 2011). Main differences among the models are attributed to evaporation and snow modules, as well as their storage components. This section briefly discusses how the model structural differences affect the results in the calculation of recurrence. *Figure 3-18* shows the boxplots containing the ranges of recurrence for every variable in all basins by the eight different models.

Marginal differences in recurrence are found in most of the tropical humid basins on the QPES class. Larger differences are observed in storage variables in these basins. For the case of Brahmaputra, GWAVA and MPI-HM are outliers in the recurrence of storage computing 0.03 and 0.55 respectively, while other models range between 0.92. and 0.96. Haddeland et al. (2011) highlighted the overestimation of evaporation on this basin due to the use of the Thornthwaite evaporation scheme used by the MPI-HM model. This leads to higher interannual variations on storage components due to higher evaporation. In the case of GWAVA, the storage series for this basin shows a cyclic increase in storage until it is abruptly decreased to a lower volume. This pattern is only observed in the snow component of storage, which is highly overestimated in GWAVA compared to other models.

Models in the temperate zone show larger differences mostly in runoff and storage recurrence. This is due to the variety of climatologies that are present in this zone and the presence of snow. Snowfall is treated differently in each GHM, with different thresholds for snowfall, and among -all models, there are different melting schemes. These differences mainly affect basins that are around the threshold zone between 0 and 1˚C, where precipitation is partitioned between snow and rain and melting processes start (Haddeland et al., 2011). Despite these large differences, most models indicate the same class for most basins. In subarctic basins, where the influence of snow is much more important, the differences are low, but the WaterGAP represents the lowest recurrent pattern of all models. This is possibly due to the degree day method. Temporal and spatial variations in snow content are larger in the WaterGAP model, decreasing recurrence. However, the relation of storage recurrence and snow amount is kept, as basins with higher snow content also- exhibit higher recurrence.

Finally, arid basins have wide ranges due to the differences in partition between evaporation and runoff in each model. The MATSIRO model is an outlier in having high recurrence in evaporation. When inspecting the time series of storage for these catchments, a marked decreasing trend was found. This can be partially attributed to the deep groundwater tank that keeps water available for evaporation despite the lack of water supply through precipitation. Evaporation follows the seasonal cycle of $E_P$ in MATSIRO, increasing recurrence. Storage also shows higher recurrence than other models despite the decreasing trend because it also contains a seasonal oscillation in a similar fashion as the schematic pattern of case 6 in *Figure 3-13*.

The WaterGAP and LPJmL models subdivided storage into more than two components, featuring a groundwater and surface storage tank. The groundwater stores water infiltrated from soil moisture deeper underground and drains directly into a lake tank. This groundwater component represents a small volume, only simulating a dynamical part of the groundwater that actually exists in a basin. Deep groundwater is not represented by these two models. The surface water storage component includes tanks for lakes, wetlands, and river channels. These tanks receive as input direct runoff, flow from the groundwater tank, and direct precipitation. The outflow from the surface water component is given by discharge onto a downstream cell. Due to the inclusion of a river channel tank, the possibility that our results are affected by the time lag in lengthy river channels exists. However, among the difference in the results shown in *Figure 3-15* and *Figure 3-18* there were no differences that could be attributable to the time lag due to the length of the river. Further analysis should be performed in order to understand the effects of the inclusion of river channel storage in the measures of recurrence.

### *3.4.4. The storage hydrologic function of basins*

The inclusion of storage and explaining its temporal variations are two of the features of this chapter. The approach adds to previous studies that have identified storage as an important component for runoff generation (Black, 1997; Sayama et al., 2011) and highlighted its interaction with precipitation and evaporation temporal patterns (Jothityangkoon & Sivapalan, 2009). The classification remarks on how storage is controlled and how it controls runoff in different classes. It is identified that for particular classes, the effects of precipitation and potential evaporation transfer more directly to runoff, while in other classes, runoff is buffered by storage. The following regional hypotheses are derived from the patterns observed among the basins used in this study.

Tropics and Subtropics:

It was identified that in this region, aridity is the key aspect that determines if whether recurrence propagates through the variables. In the most humid basins, runoff and storage will follow the same pattern as precipitation. Since evaporation is limited by energy, evaporation will reach its potential and it will mainly follow the pattern of energy (more constant as it approaches the equator). As aridity increases, energy starts to compete with water availability, making evaporation more of a dominant force. Under these conditions, the timing of the peaks in energy and water become important and are noticeable in the propagation of the temporal patterns of precipitation through the pattern of other variables. Where these cycles are out of phase, storage increases during the wet season following precipitation, but after reaching the seasonal maximum, energy demand withdraws this moisture, reducing the amount that generates runoff. In the basins that are in phase, moisture is withdrawn at the same time that it is supplied, leaving less moisture to storage variation and runoff generation. Arid basins are completely dominated by energy, and moisture is available only sporadically in high intensity events. When these events take place, all variables exhibit a peak that follows the peak from precipitation..

Temperate region:

In the temperate region, seasonality plays a major role in the hydrologic functions of basins. Precipitation is recurrent only where it is also seasonal; however, among the investigated basins, this condition only takes place in basins in phase with energy following the same functioning from the tropics. Seasonality of energy is quite marked in this region, and it is mostly concentrated in the summer. This allows for basins out of phase to have a recurrent storage even if precipitation is not recurrent. The lack of demand from energy allows for storage increase during the winter. During the summer, energy takes this available moisture, leaving less water for runoff generation. Basins in phase experience the same case as phased basins in the tropics, leaving recurrence only in evaporation because it follows the seasonality of energy.

Sub-arctic region

In the subarctic region, the functioning of basins is mostly dependent on storage. Snow is the most dominant component and accumulates over a long period of time. Regardless of the pattern of precipitation, evaporation and runoff will follow storage as energy becomes available during the spring and into summer. However, in order to sustain the patterns of runoff and evaporation, the storage amount has to be large. Hence, the functioning of the basin is not directly related to the pattern of precipitation but rather to its volume.

### *3.4.5. Implications of recurrence to hydrology and engineering*

From and engineering perspective, the behavior of runoff is of most importance. River infrastructure is usually design to withstand extreme events of a certain return period. In addition, water managers also design water supply and irrigation infrastructure and supply reservoirs depending on expected low extremes of a certain return period. Since basins with high recurrence have less departure from the annual pattern, it also means that their extremes are also not as large as in basins with lower recurrence. This would mean that if an extreme value distribution function is drawn for a basin with high recurrence in runoff and a basin with low recurrence in runoff the basins with low recurrence would have a steeper curve indicating more variability in inter annual extremes.

Additionally, the recurrence in hydrological variables can also be an indicator of the interannual variability of hydrological variables. According to the definition of recurrence, a variable with higher recurrence is less likely to have a high range of interannual variability as it should not deviate largely from the annual cycle. It can also indicate the intra annual variability of hydrological variables. In this regard, intra annual variability does not refer to the variability of having two marked extremes but that the extremes or constancy of a variable are kept in the same period of the year. Once again citing the example of *Figure 3-12*, the pattern of precipitation in the Ob river basin with low recurrence, also has greater intra annual variability since high and low extremes of different years can be accounted for in different months. Furthermore, the predictability of hydrological variables can also be related to their degree of recurrence. A highly recurrent variable is likely to follow the same pattern year after year; hence, it will be easier to predict its state at a particular part of the year.

From a hydrological science perspective, recurrence in hydrological variables has also been proven to indicate that different combinations are the result of characteristics in basins related to aridity, seasonality, synchronization of peaks in water and energy availability. Also, an important regionalization was found, meaning that it is possible to deduct certain basin characteristics by quantifying recurrence or vice versa.

Through the classification presented in this chapter, it is also possible to know which types of basins are expected to have recurrence in certain variables and it is possible for water managers to deduct that basins with certain aridity, seasonality or other characteristics, will present a certain degree of recurrence.

### *3.4.6. Limitations of the current method*

This study was carried out using a multi model dataset developed with reanalysis forcing. It is important to know that even if the differences from model to model regarding the classification were not large, and the outliers were possible to relate to particular characteristics of the models, the study is not based or compared with observations. The presented results and figures are developed from the WaterGAP model, which is the only out of the eight models to be calibrated against runoff observations. However, even this model is known to compensate errors in other variables, especially the storage components (Döll, Kaspar, & Lehner, 2003). The discrepancies from model to model are likely to exist due to compensation from different variables in order to maintain water balance (Haddeland et al., 2011). Future possibilities to test this classification include using satellite datasets, or those based in observations, such as the GPCC, GRDC, and GRACE for precipitation, runoff and storage respectively, or better yet, a combination of models, observations, reanalysis and remote sensed data.

This study also considers large river basins only (areas higher than 600,000 $km^2$). These basins possibly include several sub climates, heterogeneity in geology and soils, heterogeneity in land cover, heterogeneity in topography, and different impacts from humans. For the present study only the spatial average of hydrological variables was accounted for, meaning that the regions where these variables are larger dominate the patterns that were quantified. For example, the Niger and Nile basins have about half of its area in extremely humid and extremely dry areas. Since the magnitude of the variables in dry areas is extremely low compared to humid areas, the patterns of humid areas dominate; hence they were classified in the same class as the Amazon River. Most probably, if accounted for as sub-basins, the dry areas would be classified under different characteristics having different implications for said sub-basin.

It is hypothesize that this analysis can be also used at basins of any sizes. Within the data set, there is no evidence to think that the scale of the basins can influence the recurrence of hydrological variables as there are high and low recurrence patterns in basins of all sizes. However, smaller basins respond much faster to the hydrological cycle, especially the rainfall runoff relation can be only of a few hours. If the temporal scale of the analysis is kept at a monthly scale, it is likely that the methodology can still be applied since small basins are also likely to have high and dry periods even if every individual event is quick (i.e., there will be more events during wet months giving higher monthly totals, which should be recurrent or non-recurrent). Still, the limitation of the scale remains since smaller basins are much more sensitive to other factors such as human impacts (also ignored in the current study), and physiographic effects (e.g., impacts from lakes).

These limitations are possibilities and opportunities for future research.

### 3.5. Concluding summary

This chapter presented a framework of hydrologic classification applicable to large scale river basins based on monthly temporal variations of precipitation, evaporation, storage, and runoff. The classification was derived from the concept of hydrological recurrence as a metric defined as the degree to which a monthly hydrological variable returns to the same state in subsequent years. The recurrence was measured using the mean of AC with multiples of 12 up to 60 month lags, the intensity of FFT intensity, and

Colwell's Contingency Index. These measures were calculated at global gridded scale ($0.5^o$) and at the 35 largest basins of the world based on the WFD or the 20CMO datasets.

The recurrence of individual variables is generally different in different latitudinal regions. For the recurrence in precipitation, the seasonality of moisture plays an important role, while for that in evaporation, the effect of seasonality in energy is more dominant. Storage recurrence is more dependent on the seasonality of moisture in the tropics and snow at higher latitudes. Finally, all combinations control the characteristics of the recurrence in runoff.

According to our proposed classification, which results in 16 possible classes from the combinations of high or low recurrence of the four variables, only 10 classes are present from our study river basins. *Figure 3-19* summarizes the classes and the factors that affect them. In the tropical region, recurrence in runoff and storage is essentially dependent on aridity. Humid basins are highly recurrent in all variables. Drier basins have low recurrence in runoff but storage recurrence is dependent on the timing of the peaks in precipitation and $E_P$.

In the temperate region, evaporation is always recurrent due to high seasonality, while precipitation shows low recurrence in this region, due to basins' aridity. In these basins, the timing of peaks between $P$ and $E_P$ also influence the recurrence in $Q$ and $S$.

In the subarctic region, evaporation is again highly recurrent due to extreme seasonality. Precipitation is recurrent in areas with moisture from oceanic current influences. Recurrence in storage is in the basins with larger amounts of snow whose melting process dominates the patterns of runoff. As a result, the runoff recurrence is also high in this region, while the storage recurrence varies in different areas. Therefore, the river basins are mainly classified into QPES, QPE, QES or QE depending on their combinations.

The above results were primarily obtained based on the analysis of AC metric with the WaterGAP model output. However, the other two metrics, FFT intensity and Colwell's Contingency, and other eight models also essentially showed consistent results.

Overall the presented approach is an attempt to define basin similarity accounting for the temporal patterns of water balance components. River basins in the different classes are likely to behave differently even under the similar changes in climate control. The same framework may be applied to long-term time series data from different sources including GCM future projections. Furthermore, by using long-term time series breaking down into several partial time series, the proposed framework may identify a hydrologic regime shift from one class to another, as well as the characteristics of hydrologic sensitivity in different classes. For this kind of study, EU-WATCH provides useful datasets for projecting future hydrologic variables.

Finally, there are several limitations that are intrinsic to the classification framework. Although, some of the combinations that were not found are considered not feasible (e.g. only recurrent runoff), there are other classes that may be found if the sample of basins is further extended. The classification also considers no landscape controls in the hydrological processes, effects of land use, or human interactions among other important factors that also dominate and influence the temporal variability of hydrological variables. The framework currently uses the spatial average of large river basins, leaving aside heterogeneity in climatic and geographic characteristics. Downscaling to smaller sub-basins can bring insight not only in the behavior at smaller scale but also on how different sub-basins add up to create a general pattern in the large scale basins. Even though the presented method is not a definite and exclusive classification framework, the analysis comparing different classes provide useful insights into the functions of large river basins in the world.

Table 3-1

*Component contribution ratio (CCR) for basins located in the Subarctic region.*

| Basin | GroundMoist | SoilMoist | SurfStor | SWE |
|---|---|---|---|---|
| Yenisei | 0.056 | 0.095 | 0.247 | 0.602 |
| Lena | 0.021 | 0.076 | 0.391 | 0.512 |
| Mackenzie | 0.077 | 0.135 | 0.109 | 0.679 |
| Ob | 0.077 | 0.225 | 0.112 | 0.586 |
| Volga | 0.083 | 0.271 | 0.145 | 0.501 |
| Yukon | 0.059 | 0.052 | 0.312 | 0.577 |
| Kolyma | 0.011 | 0.034 | 0.322 | 0.633 |

*Note:* The CCR is calculated as in Kim et al. (2009).

Table 3-2

*Results of Colwell's Indices: Constancy (C), Contingency (M) and Predictability ($P_{red}$) for all variables in arid basins.*

| Basin | Variable | C | M | $P_{red}$ |
|---|---|---|---|---|
| Colorado | *P* | 0.303 | 0.110 | 0.413 |
| | *E* | 0.284 | 0.265 | 0.549 |
| | *Q* | 0.433 | 0.115 | 0.548 |
| | *S* | 0.302 | 0.209 | 0.511 |
| Darling | *P* | 0.300 | 0.073 | 0.373 |
| | *E* | 0.297 | 0.209 | 0.506 |
| | *Q* | 0.380 | 0.179 | 0.559 |
| | *S* | 0.291 | 0.170 | 0.461 |
| Grande | *P* | 0.320 | 0.173 | 0.493 |
| | *E* | 0.320 | 0.207 | 0.527 |
| | *Q* | 0.432 | 0.089 | 0.521 |
| | *S* | 0.297 | 0.077 | 0.374 |
| Orange | *P* | 0.339 | 0.176 | 0.515 |
| | *E* | 0.311 | 0.202 | 0.513 |
| | *Q* | 0.507 | 0.067 | 0.574 |
| | *S* | 0.365 | 0.077 | 0.442 |

Table 3-3

*Classification using different metrics, Autocorrelation (AC), Colwell's Contingency (M) and Fast Fourier Transform intensity (FFT intensity).*

| Basin | AC | M | FFTintensity |
|---|---|---|---|
| Amazon | QPES | QPES | QPES |
| Amur | QPE | QPE | QPE |
| Brahmaputra | QPES | QPES | QPES |
| Changjiang | QPES | QPES | QPES |
| Colorado | L | E | S |
| Columbia | ES | ES | ES |
| Congo | PE | PE | L |
| Danube | E | E | ES |
| Darling | L | L | L |
| Euphrates | ES | PES | QPES |
| Ganges | QPES | QPES | PES |
| Grande | L | L | L |
| Huanghe | PE | PE | PE |
| Indus | E | E | L |
| Kolyma | E | QE | E |
| Lena | QPE | QPE | PE |
| Mackenzie | QPE | QPE | PES |
| Mekong | QPES | QPES | QPES |
| Mississippi | ES | ES | ES |
| Nelson | E | E | PES |
| Niger | QPES | QPES | QPES |
| Nile | QPES | QPES | QPES |
| Ob | QES | QES | ES |
| Okavango | PE | PE | PE |
| Orange | L | L | L |
| Orinoco | QPS | QPS | QPES |
| Plata | PE | PE | PES |
| Sao Francisco | E | E | PES |
| St. Lawrence | E | E | ES |
| Syr Darya | ES | ES | ES |
| Tocantins | PES | PES | QPES |
| Volga | QES | QES | ES |
| Yenisei | QPES | QPES | PES |
| Yukon | QE | QE | QE |

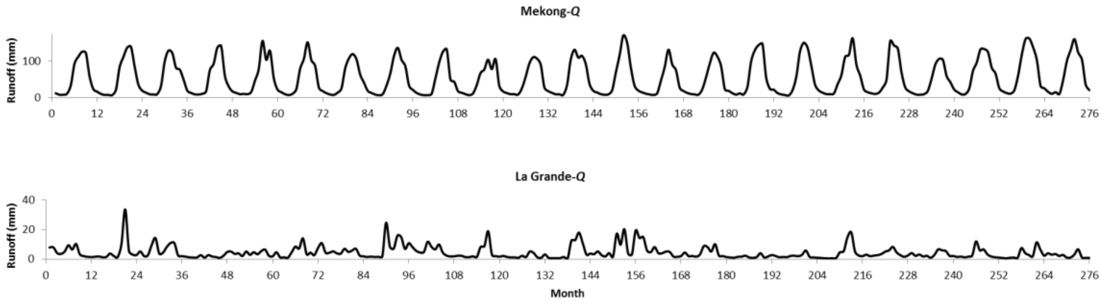



*Figure 3-1* Schematic representation of different levels of recurrence in runoff ($Q$) time series the Mekong and La Grande river basins.

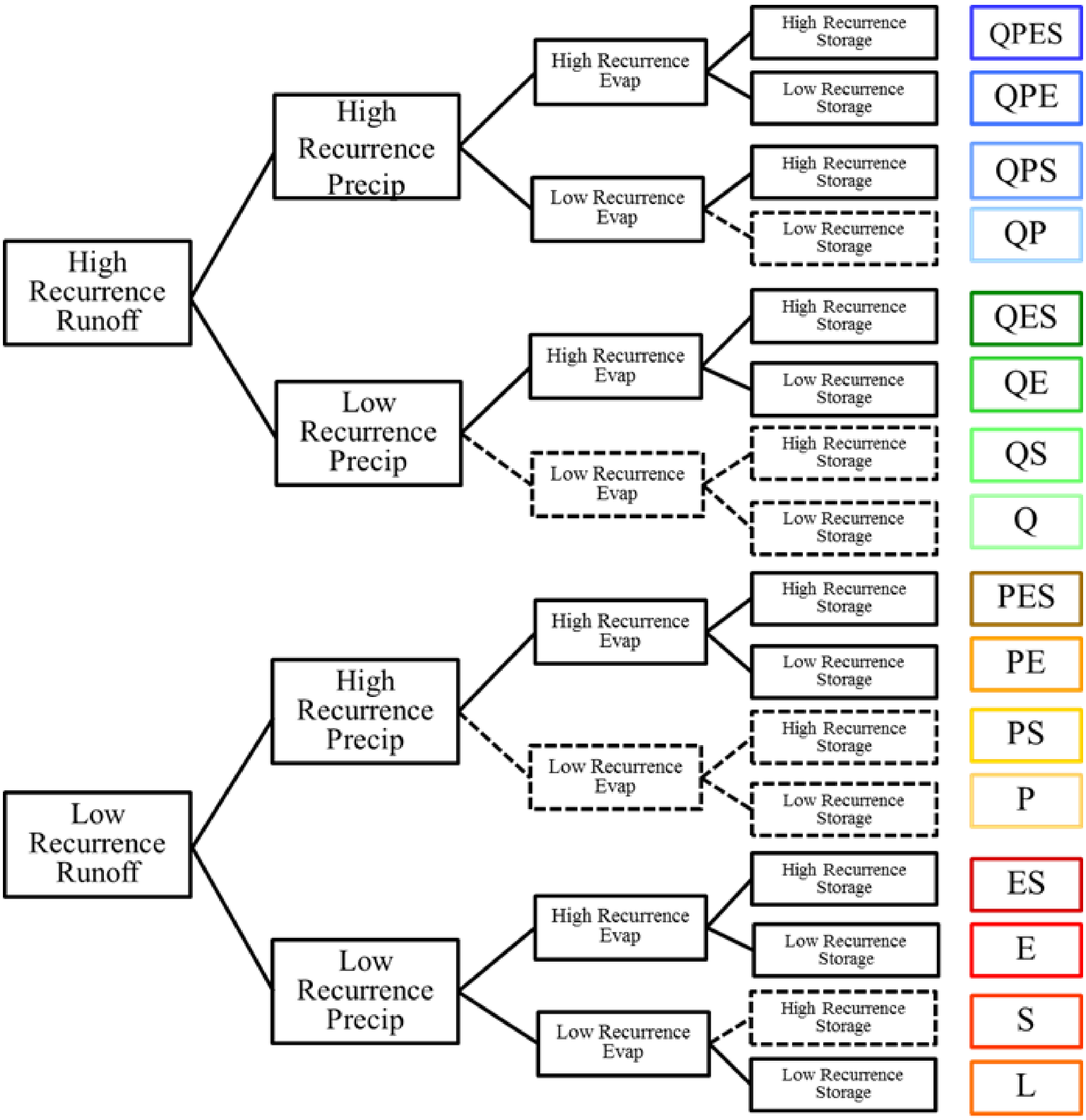



*Figure 3-2* Hydrological classification tree. Color codes indicate the colors used in further maps to identify the classes to which basins belong. Dashed lines indicate paths into classes that were not found in the studied basins.

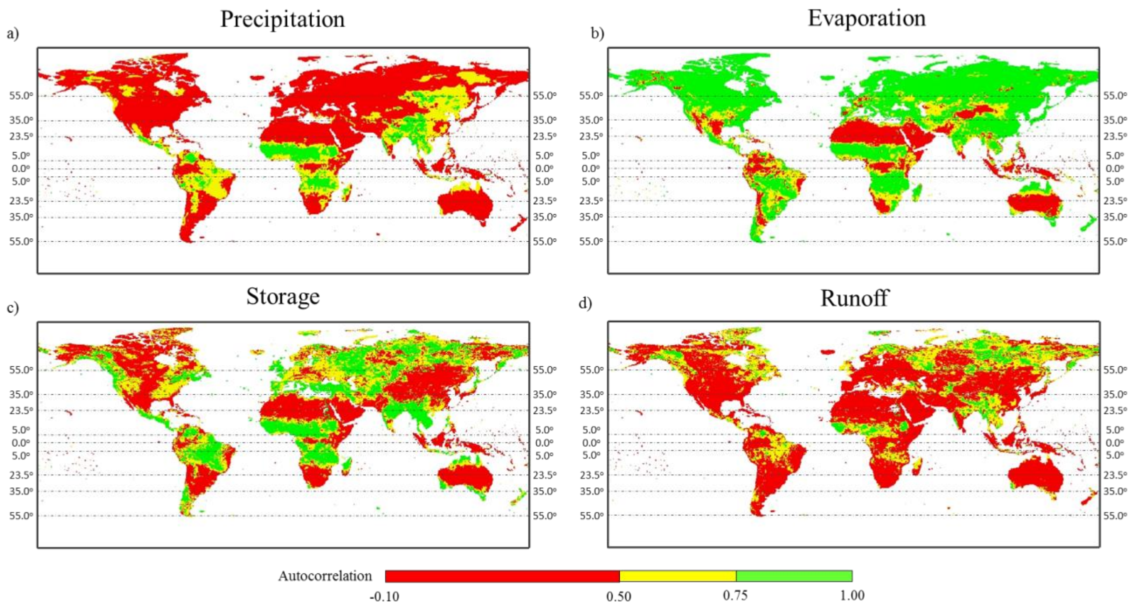



*Figure 3-3* Recurrence (AC) in main hydrological variables at global scale: (a) precipitation, (b) evaporation, (c) storage and (d) runoff. The map identifies the areas with lowest recurrence (< 0.5), low recurrence (0.5–0.75) and high recurrence (0.75 <). Reference latitude lines identify the divisions in latitudinal regions where particular conditions and similarities were found to exist. The results shown in this figure are based on the WaterGAP model output only.

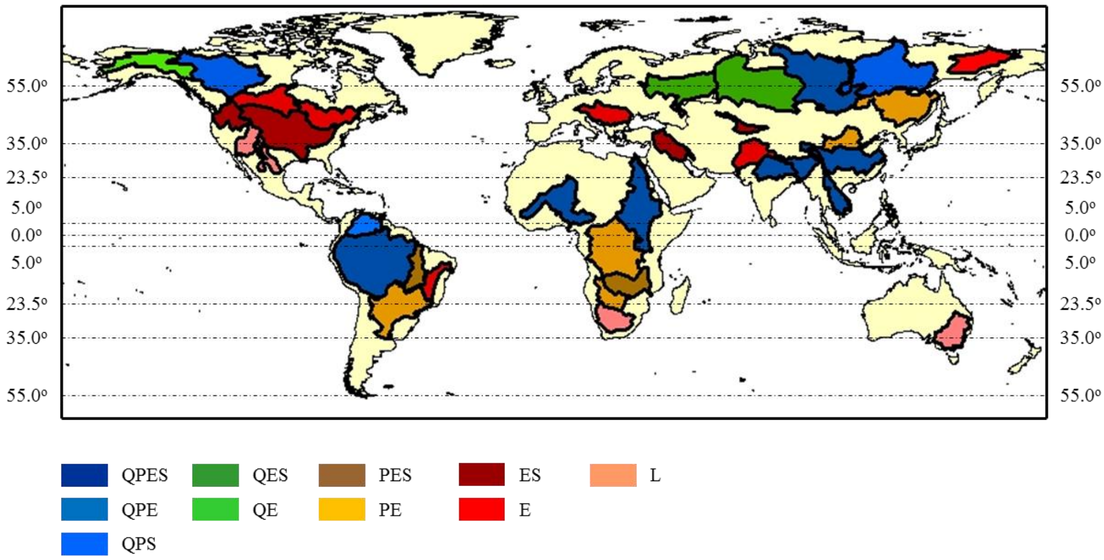



*Figure 3-4* Basin location map with identification by class. A threshold for defining high recurrence or low recurrence was set at 0.75. Latitude regions were defined between the reference lines shown on the map for both hemispheres delimiting the tropical region between 0.0 and 23.5, subtropical region between 23.5 and 35.0, temperate region between 35.0 and 55.0 and subarctic and arctic regions greater than 55.0°. This map is based on the results of the WaterGAP model only.

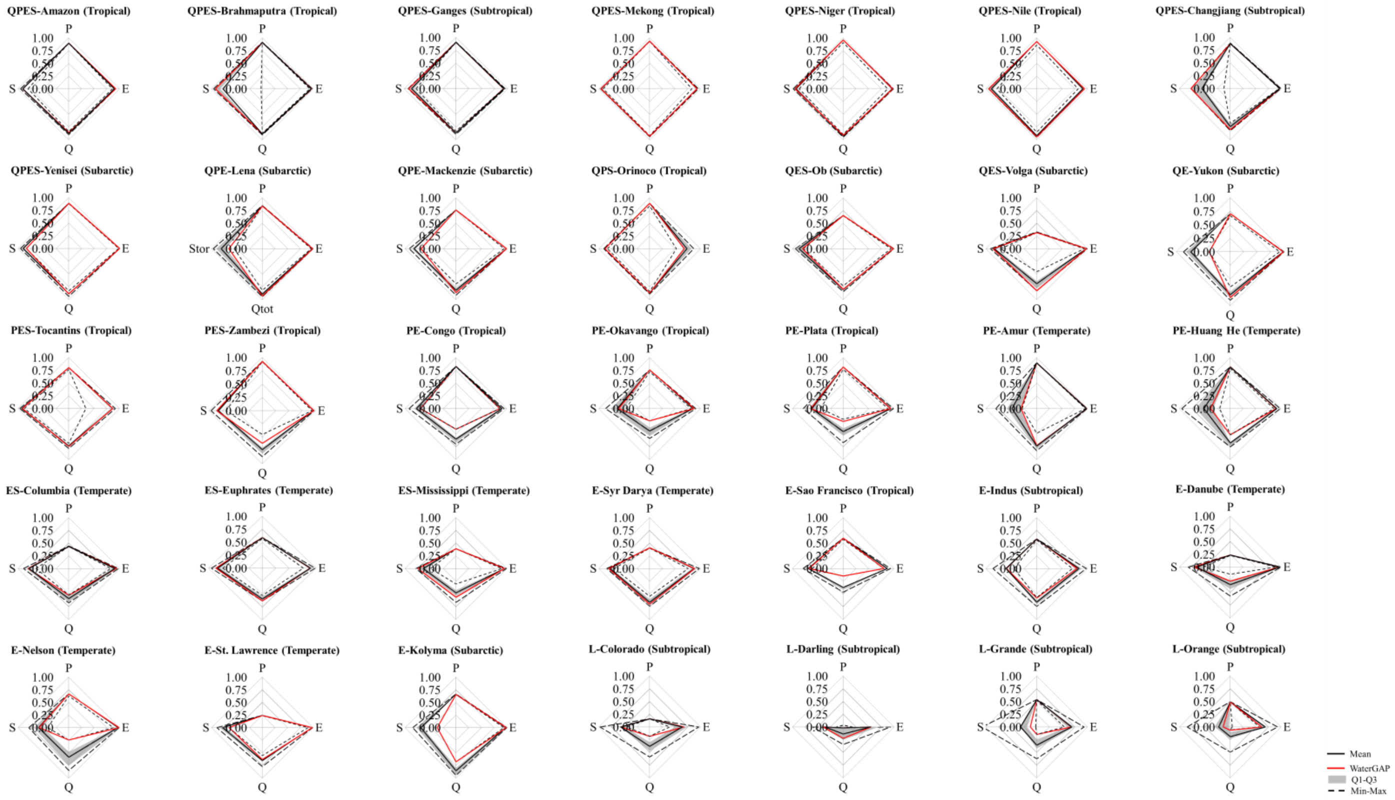



*Figure 3-5* Radar charts depicting the results of recurrence for each variable in each individual basin. Results from the WaterGAP model are highlighted in red, the model mean is shown as a solid black line, the interquartile is shaded in gray, and the max. and min. values are shown with a dashed black line.

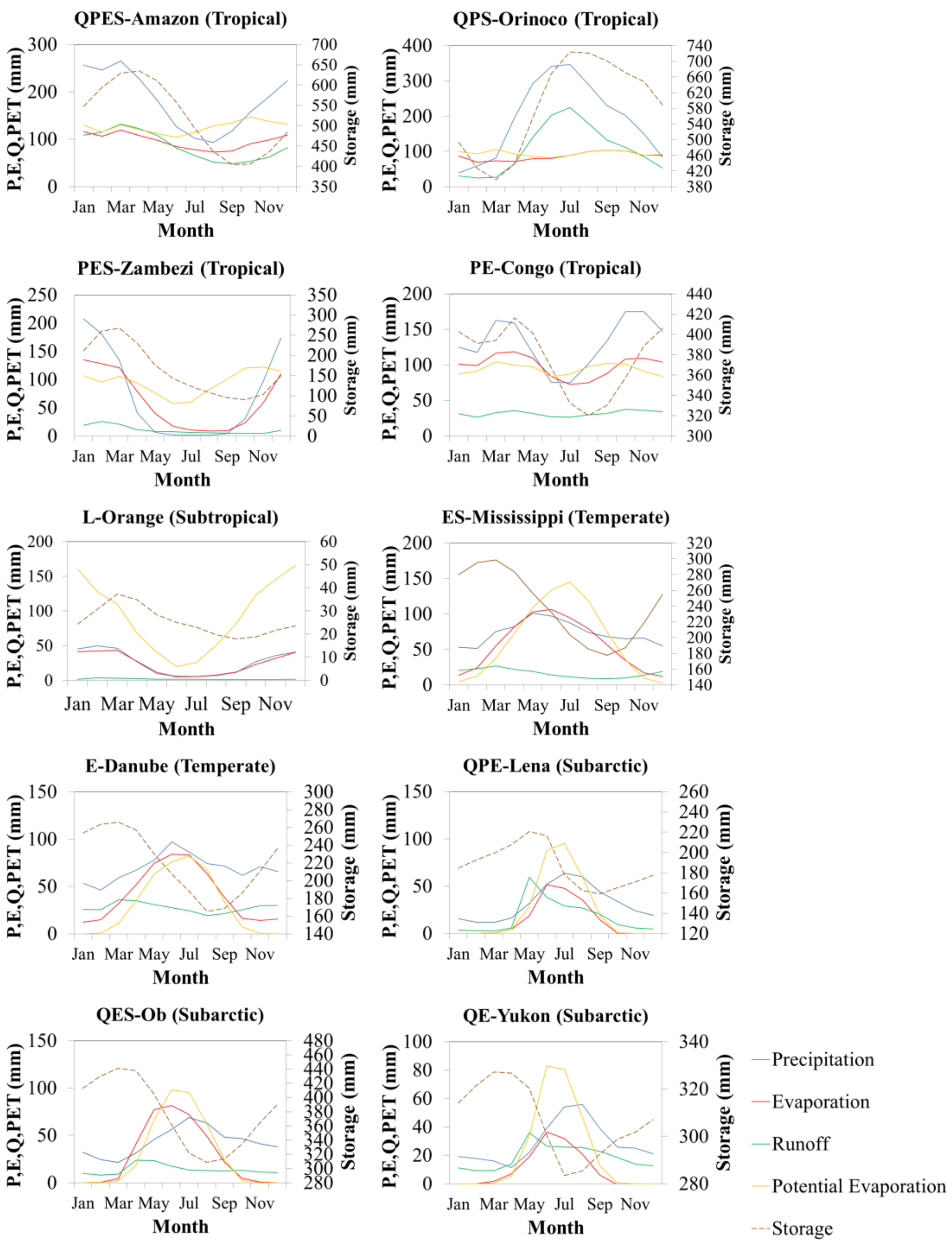



*Figure 3-6* Variable climatologies for selected basins for each class and region. The charts present a particular basin for each of the 10 classes found sorted by region. Comparable axis of precipitation, evaporation, runoff, and potential evaporation are shown on the left vertical axis and storage axis is shown on the right vertical axis.

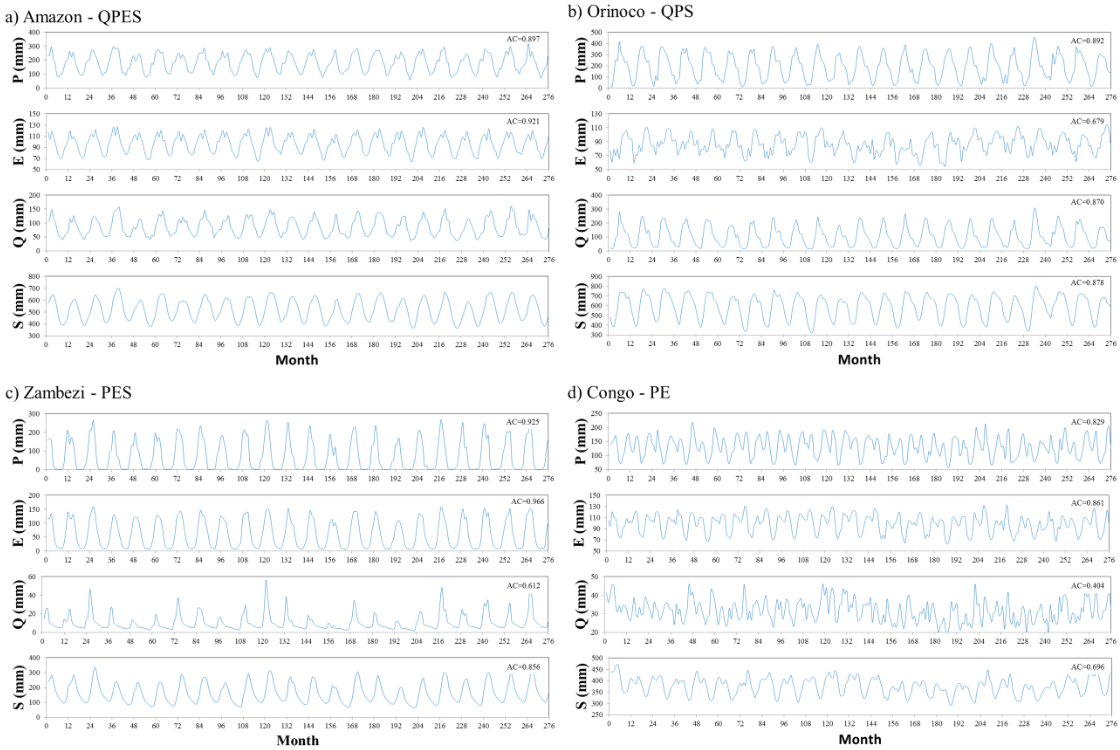



*Figure 3-7* Monthly time series of selected basins in the tropics from each class: (a) Amazon – QPES, (b) Orinoco – QPS, (c) Zambezi – PES, (d) Congo – PE. The graphs exemplify time series with high or low recurrence depending on the classification. The averaged AC coefficient is provided in the top right corner of each graph.

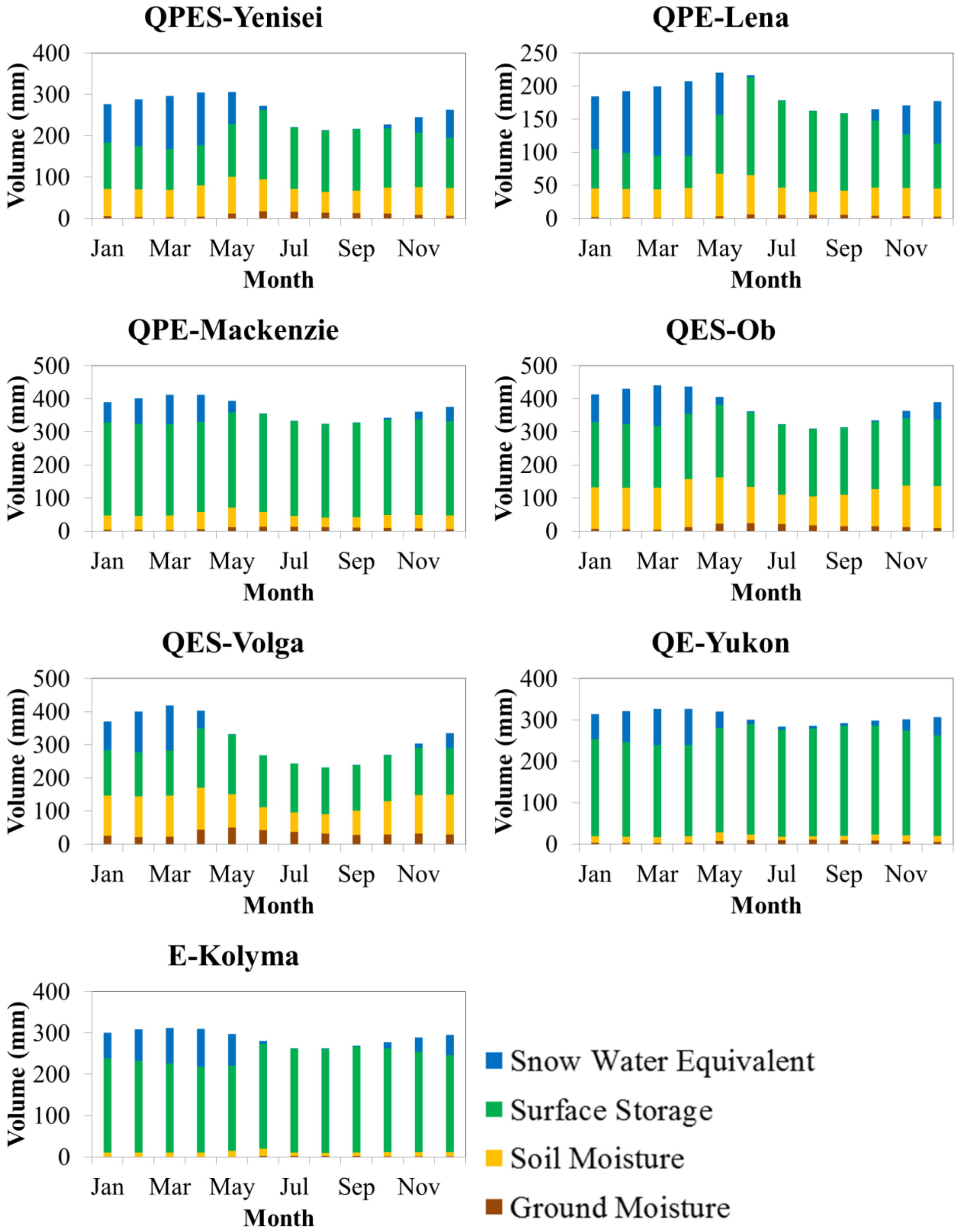



*Figure 3-8* Climatology of storage and the various storage components for subarctic basins.

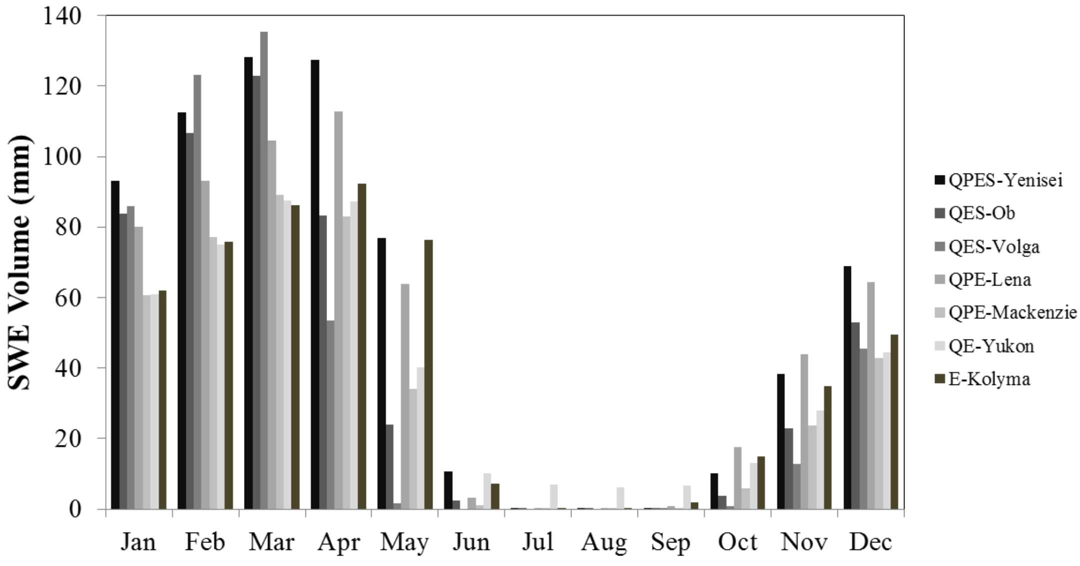



*Figure 3-9* Snow water equivalent seasonality of subarctic basins.

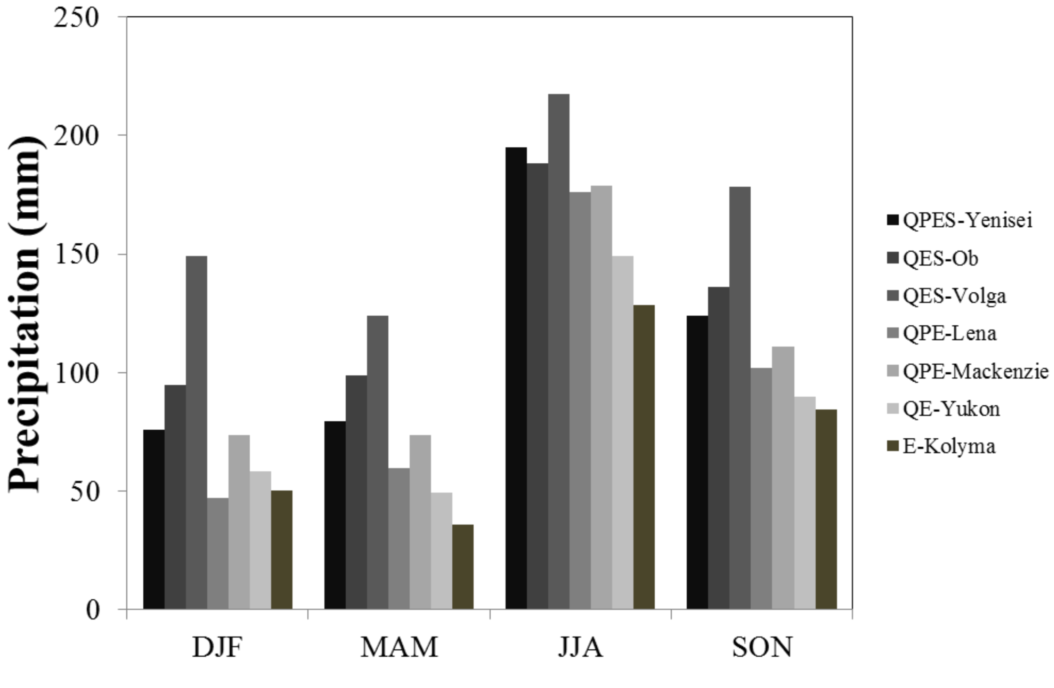



*Figure 3-10* Seasonal precipitation climatology of subarctic basins.

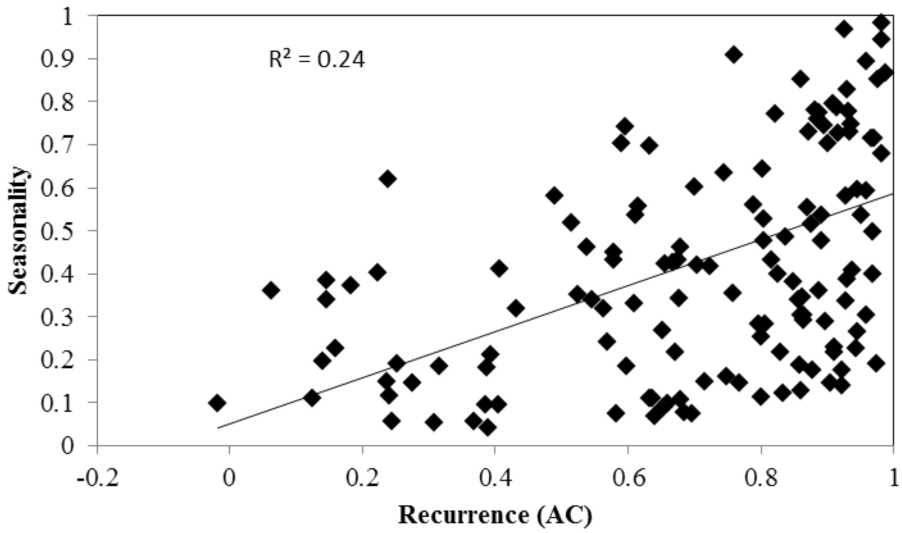
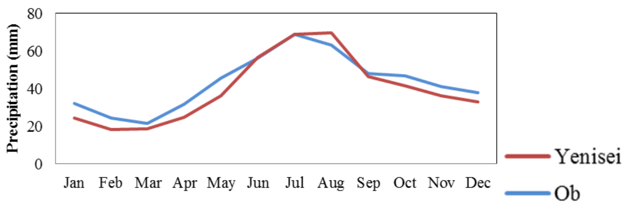
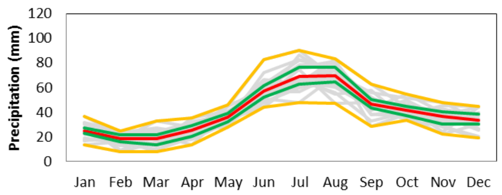



*Figure 3-11* Relationship between recurrence and seasonality from all of the time series corresponding to each variable in each basin.

**a) Climatologies**




**b) QPES-Yenisei**




**c) QES-Ob**

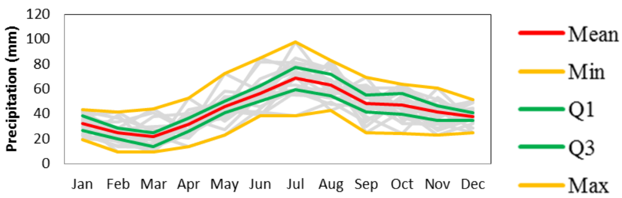
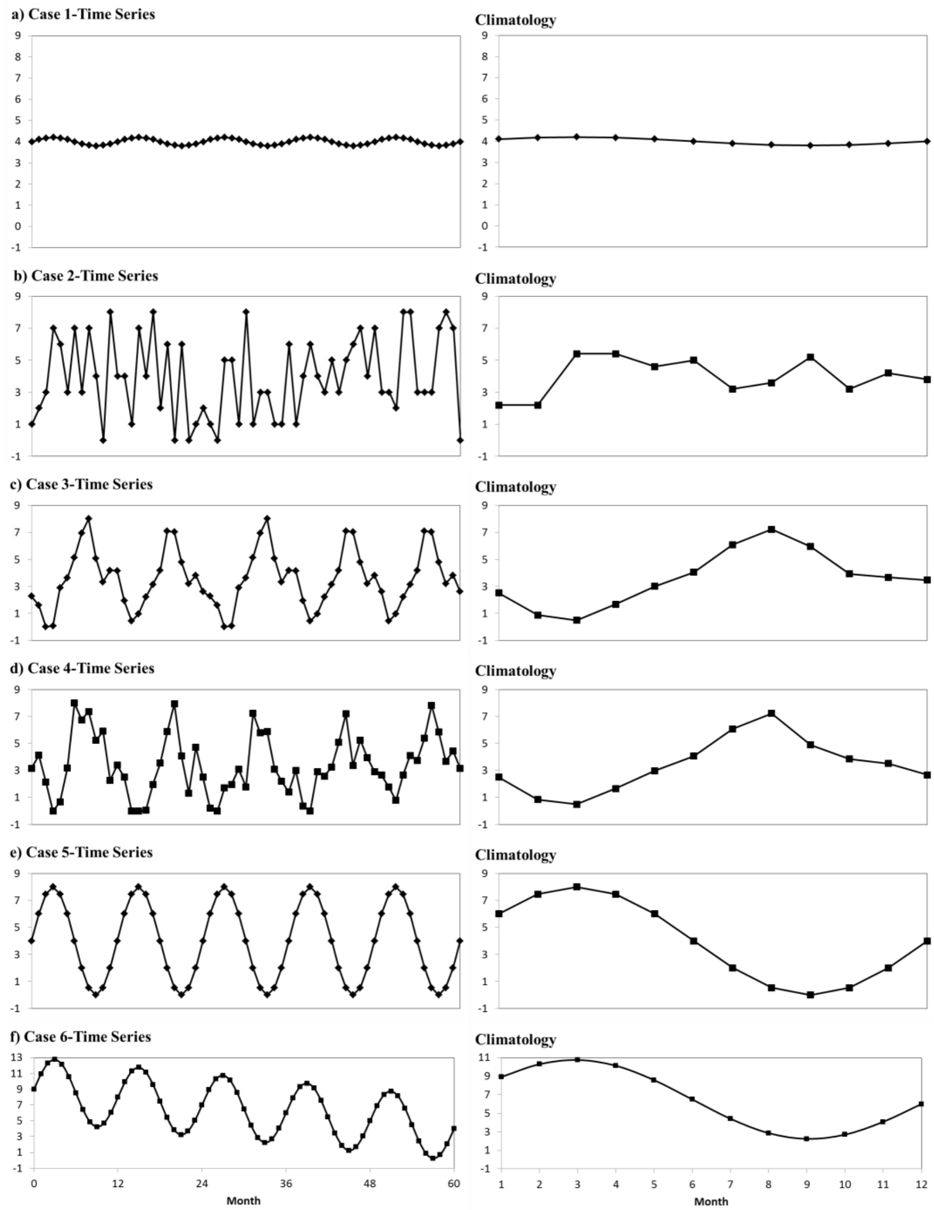



*Figure 3-12* Seasonal climatologies of precipitation in Yenisei and Ob river basins (a), long-term mean (b), and (c) 23-year precipitation in Yenisei and Ob river basins. (b) and (c) show the minimum, maximum quartiles and mean for each month.




| Case | Seasonality | Standard Deviation | Recurrence (AC) |
|---|---|---|---|
| Case 1 | 0.031 | 0.14 | 1.000 |
| Case 2 | 0.242 | 2.53 | 0.093 |
| Case 3 | 0.410 | 2.15 | 0.843 |
| Case 4 | 0.410 | 2.22 | 0.690 |
| Case 5 | 0.622 | 2.82 | 1.000 |
| Case 6 | 0.789 | 3.38 | 1.000 |

*Figure 3-13* Schematic time series representing different levels of recurrence, variability and seasonality.

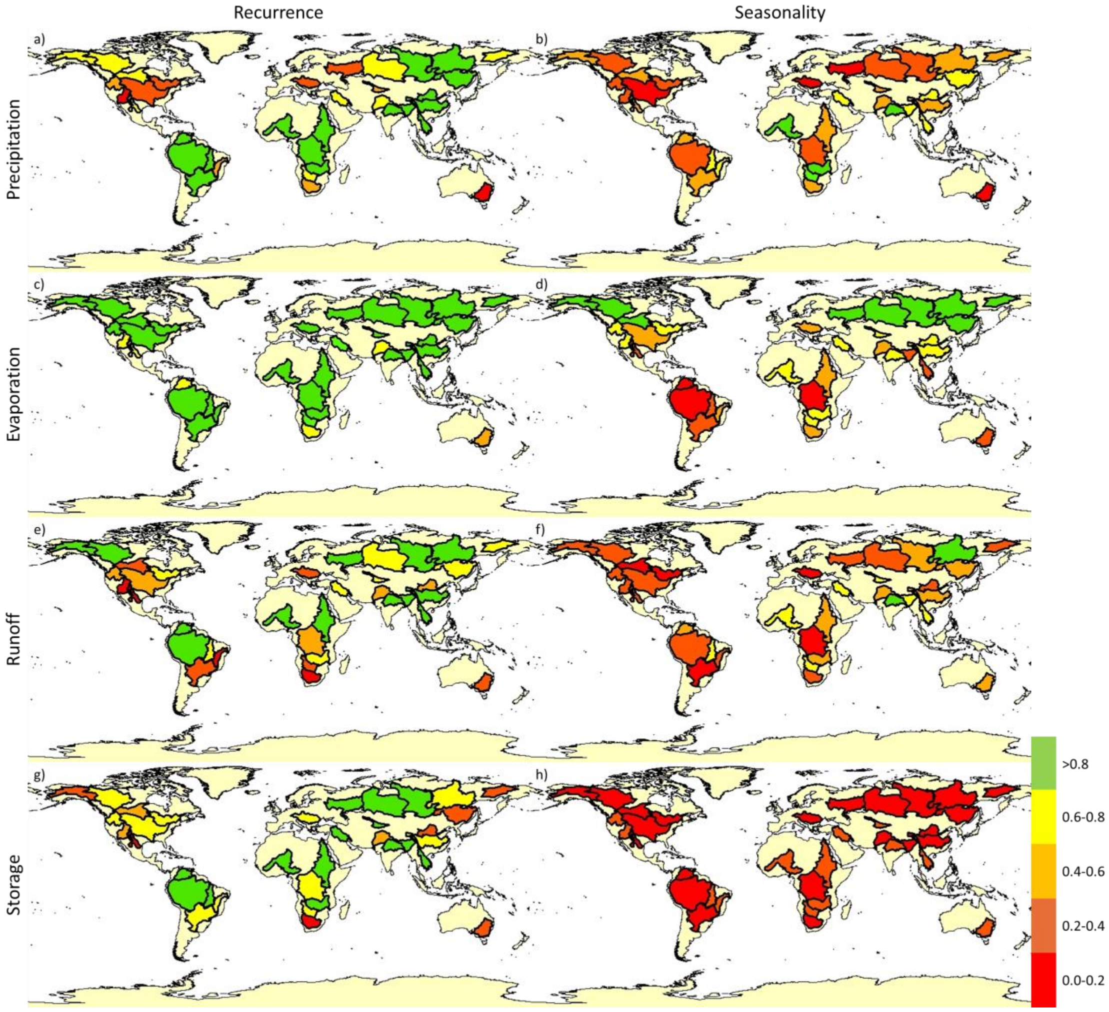



*Figure 3-14* Global comparison of recurrence and seasonality. (a) Recurrence of precipitation, (b) seasonality of precipitation, (c) recurrence of evaporation, (d) seasonality of evaporation, (e) recurrence of runoff, (f) seasonality of runoff, (g) recurrence of storage, (h) seasonality of storage. Recurrence and seasonality use the same color scale.

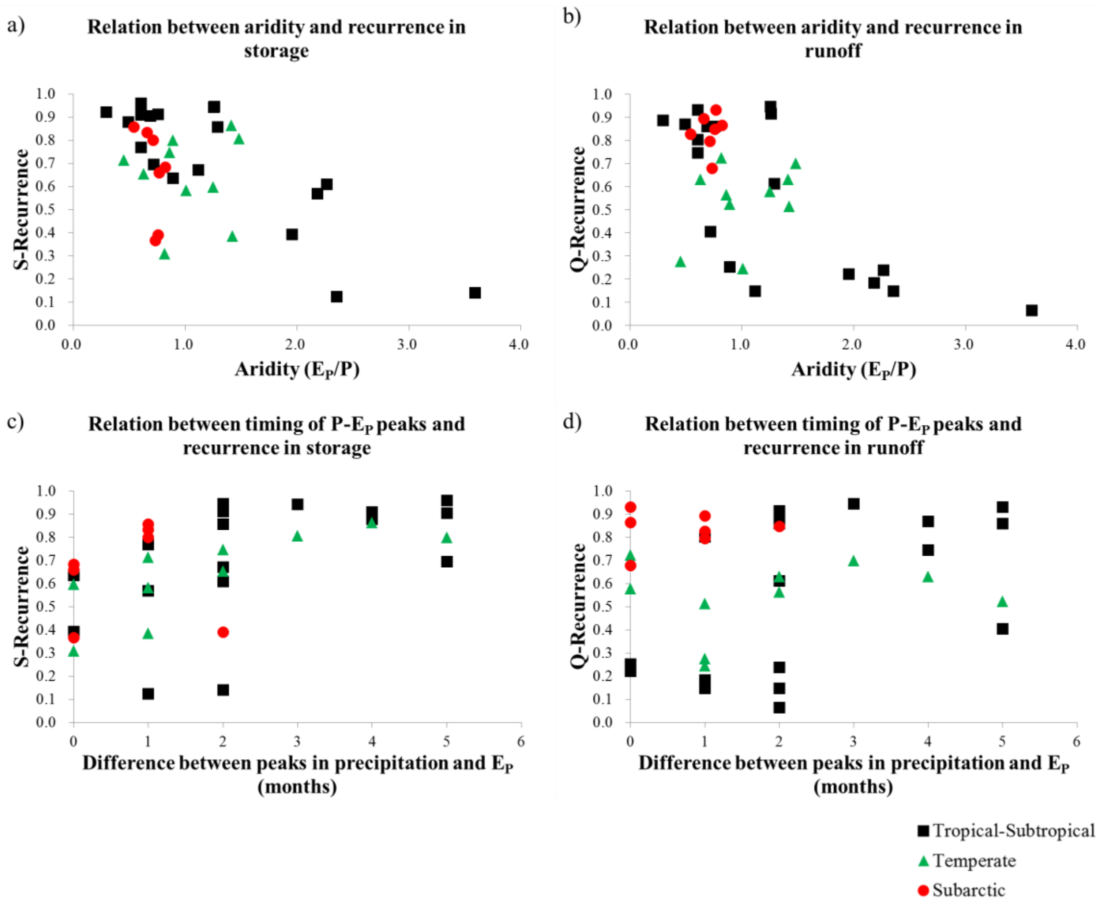



*Figure 3-15* Relation of Aridity and Timing of peaks and recurrence in runoff and storage. (a) Timing of $P$ and $E_P$ with recurrence in storage, (b) relation of timing of peaks in $P$ and $E_P$ peaks and recurrence in runoff, (c) relation of aridity and recurrence in storage., and (d) relation between aridity and recurrence in runoff.

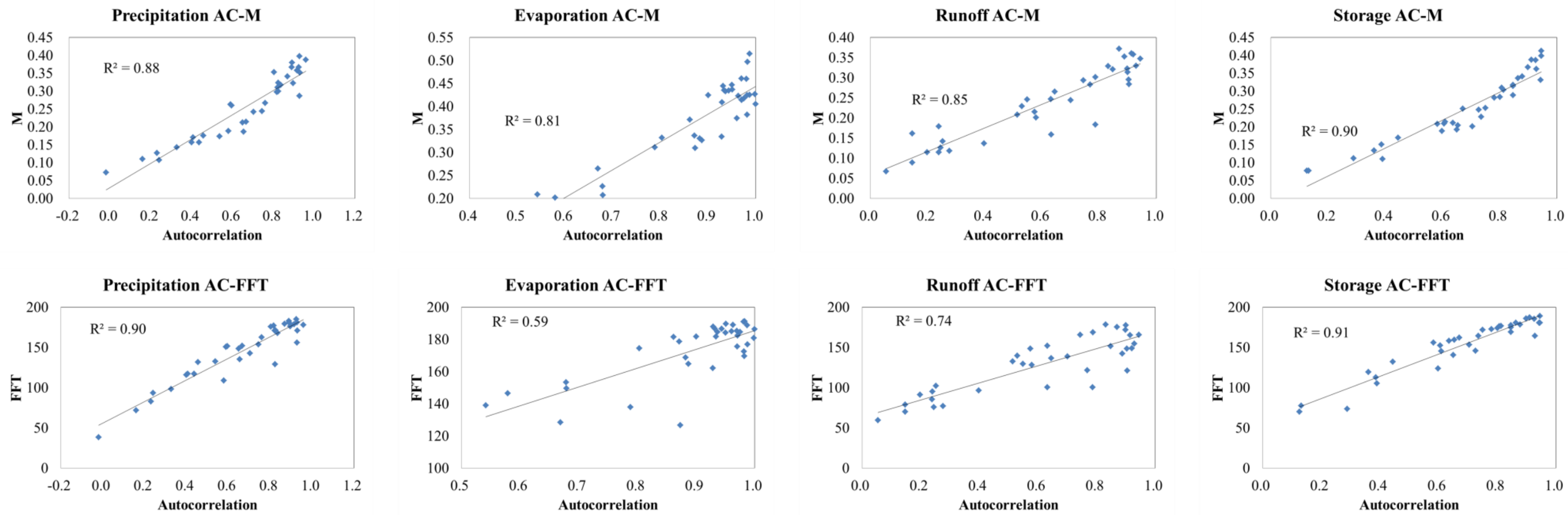



*Figure 3-16* Comparison of AC with Colwell's contingency (M), and FFT intensity.

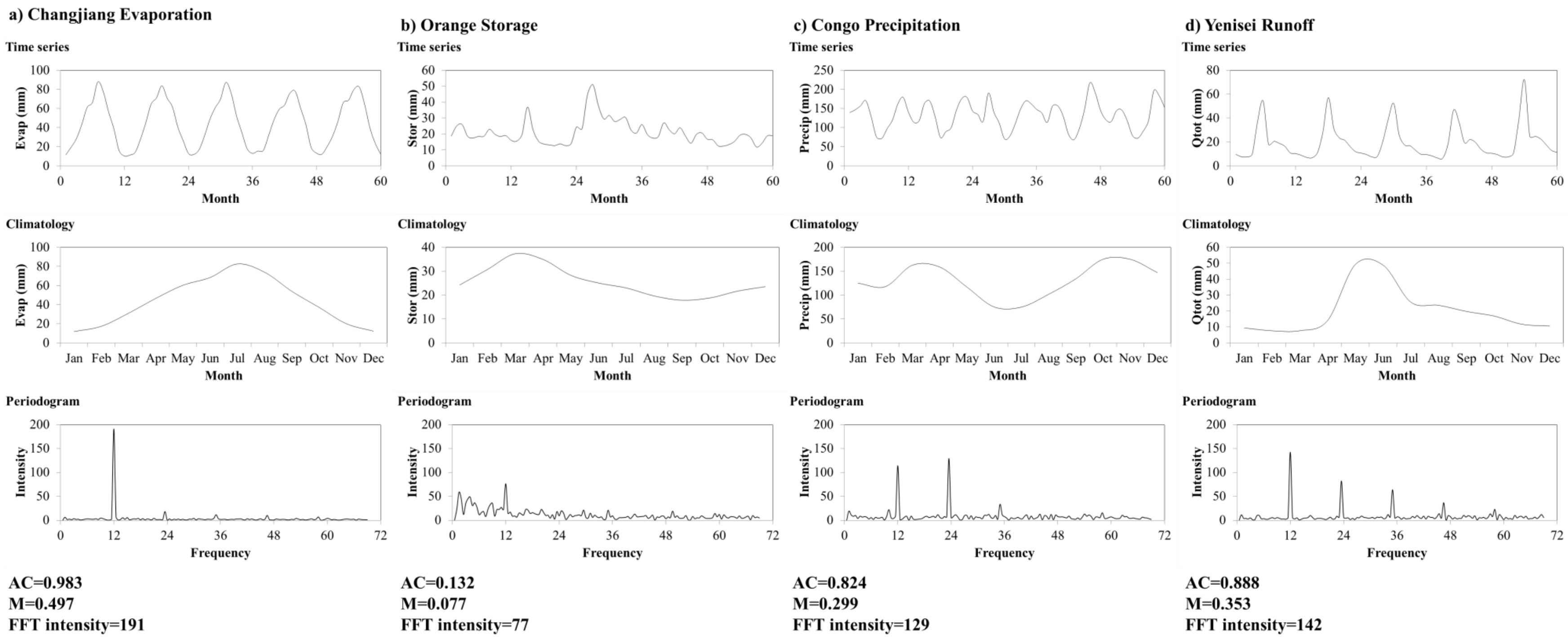



*Figure 3-17* Examples of variables with different results in FFT intensity. (a) Changjiang's evaporation, (b) runoff in Yenisei, (c) precipitation in Congo and (d) storage in Orange.

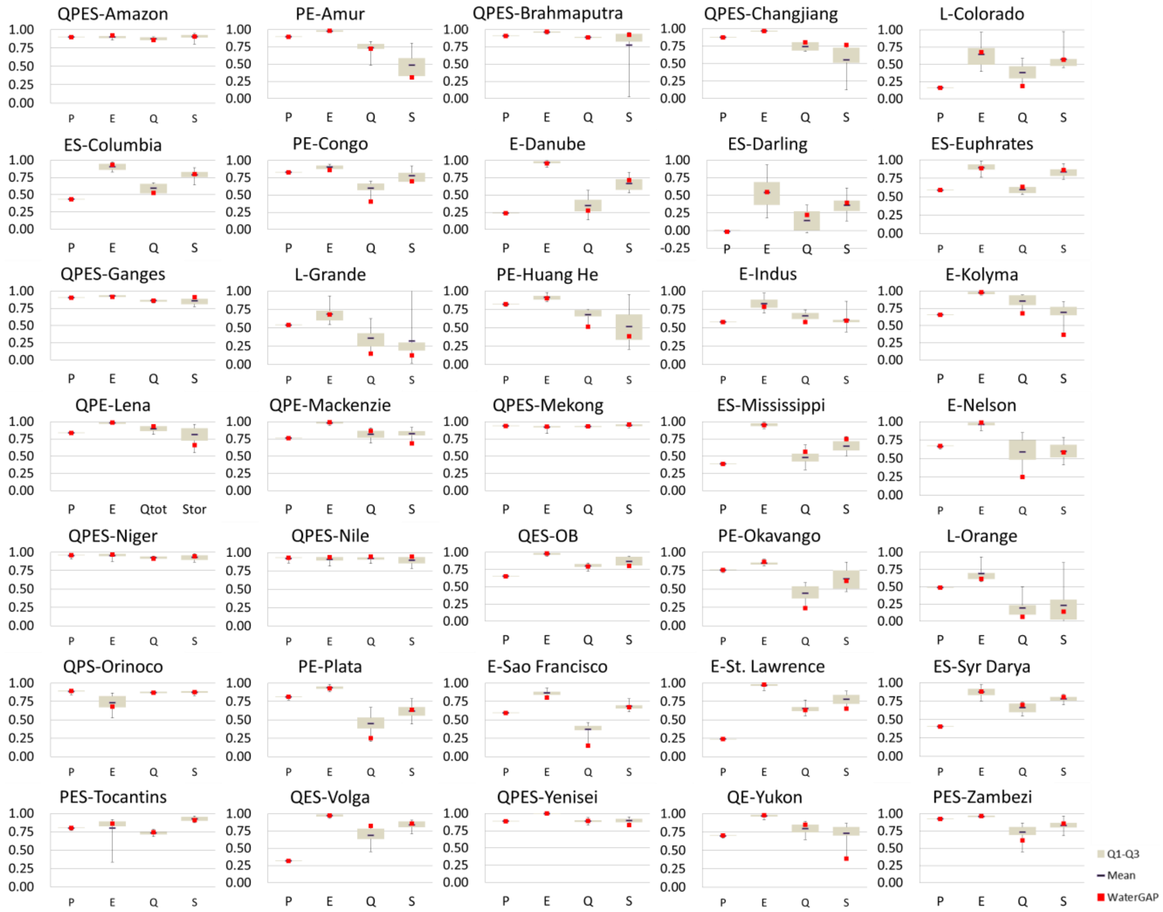



*Figure 3-18* Model differences. Box plots show the recurrence measure for each variable in each basin displaying an interquartile uncertainty band, WaterGAP marked by the red spot, the mean highlighted by the black mark and the maximum and minimum values.

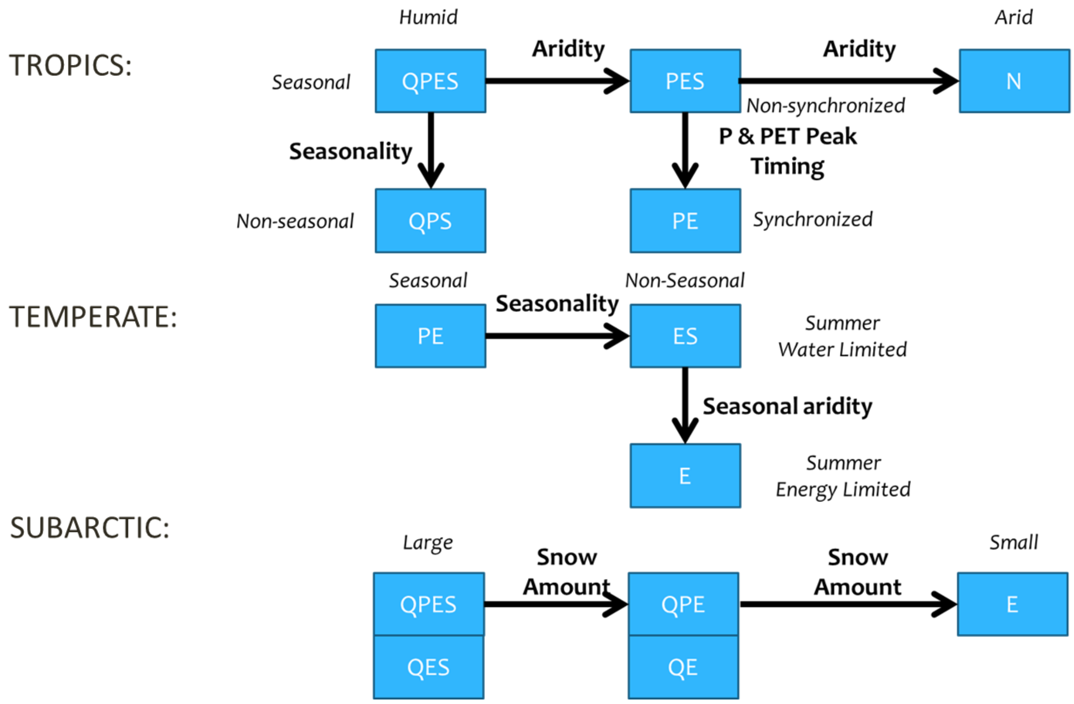



*Figure 3-19* Summary of classes based on recurrence and the basin characteristics that were found to influence the differences between classes.

# 4. The effect of climate change in the hydrological functions: Comparing process complexity vs. conceptual simplicity in future runoff projections

Parts of the contents of this chapter, including figures and tables, have been submitted for publication in *Hydrological Research Letters* and are currently under review (Fernandez & Sayama, 2015a).

## 4.1. Introduction

### *4.1.1. Process complexity: hydrological modeling*

How will climate change affect the runoff of a basin? This question is the source of many studies within the hydrological sciences. A common approach to address this question is through the use of HMs driven by outputs of GCMs with different scenarios (Field & Van Aalst, 2014). This approach has wide acceptability since both GCMs and HMs are process based models that simulate the climate and land surface conditions to a certain degree of accuracy (Alcamo et al., 2003; Bondeau et al., 2007; Déqué et al., 1994; Déqué & Piedelievre, 1995; Fichefet & Maqueda, 1997; Hagemann & Dümenil, 1997; Hagemann & Gates, 2003; Hourdin et al., 2006; Jungclaus et al., 2006; Madec et al., 1998; Rost et al., 2008; Royer et al., 2002), and provide spatial and temporal variations of water fluxes and storages for detailed analysis (Haddeland et al., 2011). Additionally the variety of GCMs and HMs allows completion of ensemble comparisons of multiple climates, from local to global scales (Haddeland et al., 2011; Haddeland et al., 2014; Hagemann et al., 2013). However, since each model has its own emphasis with different theoretical backgrounds, the projection results usually show a wide range depending on the choice of models and their settings (Beven, 2006; Lo, Famiglietti, Yeh, & Syed, 2010; Müller Schmied et al., 2014; A. Y. Sun, Green, Swenson, & Rodell, 2012). Therefore, their use and interpretation require high levels of expertise in order to improve calibration, reduce equifinality, and guarantee process based results. Moreover, atmospheric and hydrological models can be computationally expensive, as the numerical methods used within them require a large amount of iterations, updating variables, and storing all the relevant time series (Bierkens et al.; Kollet et al., 2010; Kumar, Livneh, & Samaniego, 2013; Maxwell, 2013; Yamazaki, Almeida, & Bates, 2013)

### *4.1.2. Conceptual simplicity*

Instead of using process based models, simpler analytical frameworks have been proposed. One of the approaches has been based on the Budyko framework which uses the water and energy balance concepts to define the partition of precipitation into evaporation and runoff (Budyko, 1974). The climatic variables that govern water and energy availability are the variables likely to change due to global warming making the Budyko type equations an adequate tool to analyze these changes (Roderick & Farquhar, 2011). Several functional forms of the Budyko equation exist as nonparametric (Budyko, 1974; Ol'Dekop, 1911; Pike, 1964; Schreiber, 1904), or parametric (including catchment properties) (Choudhury, 1999; B. Fu, 1981; Mezentsev, 1955; X. Zhang, Harvey, Hogg, & Yuzyk, 2001) which have evolved throughout the years depending on the application or to improve the accuracy of the method. Some examples of the evolution of the water and balance relation are introduced in Table 4-1.

The changes in climate through Budyko type studies have been carried out usually by separating a time series into two periods and comparing the changes in characteristics from both periods, either with observations (Jiang et al., 2015; Liang & Liu, 2014; Liu & McVicar, 2012; Xu, Yang, Yang, & Lei, 2014; H. Yang, Yang, & Hu, 2014; Z. Zhang, Chen, Huang, & Zhang, 2014) or using modelled data (Y. Sun, Tian, Yang, & Hu, 2014). Some of the detected changes are easily attributable to climate through precipitation or potential evapotranspiration and have been analyzed through sensitivity frameworks (Roderick & Farquhar, 2011). However, the changes in mean annual *P* and *Ep* do not entirely explain the changes in *Q*, hence much of the study has been dedicated to analyze the change in catchment properties and attribute it through the catchment parameter. In general, the catchment properties can encompass any characteristic that would have any influence in the partition of precipitation into evaporation and runoff but mostly refers to the changes in vegetation (Chen, Alimohammadi, & Wang, 2013; Donohue, Roderick, & McVicar, 2007; Li, Pan, Cong, Zhang, & Wood, 2013; D. Yang et al., 2009; Lu Zhang, Dawes, & Walker, 2001), or rainfall patterns  (Li, 2014; L Zhang et al., 2004). Most of these studies have been applied at single basins (Donohue, Roderick, & McVicar, 2011; Jiang et al., 2015; Liang & Liu, 2014; Liu & McVicar, 2012; Roderick & Farquhar, 2011; Xu et al., 2014; Z. Zhang et al., 2014) or under varied climatologies within a region: the United States (Carmona, Sivapalan, Yaeger, & Poveda, 2014; Chen et al., 2013; Istanbulluoglu, Wang, Wright, & Lenters, 2012; D. Wang & Hejazi, 2011), Australia (Donohue et al., 2007; Donohue, Roderick, & McVicar, 2010; Donohue, Roderick, & McVicar, 2012; Teng, Chiew, Vaze, Marvanek, & Kirono, 2012), China (Cong, Zhang, Li, Yang, & Yang, 2015; Xiong & Guo, 2012; D. Yang et al., 2009; D. Yang et al., 2007; H. Yang & Yang, 2011; H. Yang et al., 2014; Yu et al., 2013) and Europe (Oudin, Andréassian, Lerat, & Michel, 2008; Velde et al., 2014). The framework has also been applied at the global scale in a variety of studies to develop functional forms (Arora, 2002; Koster & Suarez, 1999; L. Zhang et al., 2001) or study the catchment properties parameter (Li et al., 2013; Williams et al., 2012).

#### *4.1.3. The need of a comparison*

Despite all the literature exploring hydrological change through the Budyko type equations, the comparison of these projections to projections with models has been limited (Roderick, Sun, Lim, & Farquhar, 2014; Teng et al., 2012). Teng et al. (2012) used a hydrological model to generate hydrological projections for Australia driving them with the output of 15 GCMs and compared it to Fu's equation (Table 4-1). They concluded that the Budyko equation is suitable for estimating climate change impact on mean annual runoff over large regions as the projections using it were similar to the projections from hydrological models, and mainly were inside of the spread of results with different GCMs. They also found biases in particular regions, but their study was limited to Australia. Roderick et al. (2014) compared the Budyko framework using Choudhury's equation (Table 4-1) to projected GCM ensemble mean changes at a gridded global scale. In general, they found that not did only the models' output follow a Budyko relation but also that the projection of changes with the Budyko framework and GCM projections was in good agreement. Roderick et al. (2014) did not do a detailed regional comparison aside from using an approximation of P-E only from GCMs. Still missing from the literature is an extensive comparison of the projections of Budyko framework and models using multi scenario, multi-GCMs, and GHMs to compare the performance of Budyko at different global climatologies.

This chapter presents the performance of the projections made with the simple Budyko framework against detailed and process based projections from a global hydrological model. The selected model is the Lund-Potsdam-Jena managed Land (LPJmL) global hydrological model (Gerten, Schaphoff, Haberlandt, Lucht, & Sitch, 2004; Rost et al., 2008). The choice of the model was bound by the data requirements of the Budyko framework (particularly that potential evapotranspiration be provided) and the availability of the model output data at the time when the study was carried out. Additionally, the LPJmL model contains one of the most detailed storage schemes within the dataset, which allowed us to explore possible storage change characteristics in the projections. The objective is to determine whether the ignoring processes such as seasonality and storage characteristics (Budyko) represents similar results as an approach that considers them (HMs). Specifically, Budyko equation's performance with respect to the models regionally and climatologically is tested. The literature using Budyko to project into the future is massive but it is important to know how it performs with respect to physically based models, what types of basins it can represent better, and the reasons for the differences between projections from HMs and Budyko. It is believed that different basins subject to different climates have different reactions in the whole hydrological cycle which can result in Budyko equation behaving in a particular fashion respective to the models. Finally, the reasons for the particularities in the tendencies of the Budyko framework are discussed by analyzing the changes in storage and seasonality that the model is able to reproduce. Possible errors and biases from Budyko equation can be the result of changes in the state variables of the basins when they are subjected to persistent trends in climatological variables adjusting the hydrological functioning to the new conditions.

## 4.2. The method for comparison

This section describes the regional division for this chapter and the methods to calculate the projection from the Budyko type framework, assess the statistical significance of projected changes by models, and assess the errors of the projections using Budyko's equation with respect to the models' projection.

### *4.2.1. Regions*

The regional division used for this chapter is described as follows:

- *Humid tropics* (HT): basins within the latitudes -23.5$^{o}$ and 23.5$^{o}$ or are affected by tropical climate such as the Brahmaputra and Ganges basin, and that have precipitation higher than 750 mm

- *Dry basins (Dry)*: Considered for any latitude having an aridity index higher than 2 and precipitation less than 750 mm
- *Temperate basins* (Temp): Considered as non-dry basins in the latitudes between 23.5$^o$ and 55$^o$
- *Subarctic basins* (SA): Considered as basins with the majority of its area above the latitude 55$^o$.

### *4.2.2. Budyko equation and projection to climate change*

As mentioned above, the Budyko framework is a model to represent the partition of precipitation into evaporation and runoff based on the water and energy balance:

$$E = f\left(P, E_P\right) \tag{4-1}$$

There have been mainly two branches of Budyko-type equations that have evolved into several functional forms resulting from the application given in the afore mentioned studies and the region of application. One branch has worked with the functional form of B. Fu (1981), exemplified in the works of Potter, Zhang, Milly, McMahon, and Jakeman (2005); D. Yang, Sun, Liu, Cong, and Lei (2006); D. Yang et al. (2007); L Zhang et al. (2004). Fu's equation (Table 4-1)can be rewritten as:

$$E = P + E_p - \left(P^{\omega} + E_P^{\omega}\right)^{1/\omega} \tag{4-2}$$

The other branch (Bagrov, 1953; Mezentsev, 1955; Milly & Dunne, 2002; Pike, 1964; Turc, 1954), is generalized in the form of Choudhury (1999), and re-written from Choudhury's equation (Table 4-1):

$$E = \frac{PE_P}{\left(P^n + E_P{}^n\right)^{1/n}} \tag{4-3}$$

Both functional are characterized by including parameters $\omega$ and $n$ to represent catchment characteristic and were unified by a linear relationship (H. Yang, Yang, Lei, & Sun, 2008). For the current study we select equation (4.3) known as the Mezentzev-Choudhury-Yang (MCY) functional form.

Based on the Budyko formula, future runoff was projected as described in the following steps. First, the parameter $n$ was estimated using the current climatic variables, including $P$, $E_P$, and $E$ obtained from the WDD and 21CMO datasets. Then, future runoff ($P$-$E$) was calculated from the projected climatic variables (i.e., future $P$ and $E_P$) with the estimated parameter $n$. Note that the procedure imitates one procedure to project future runoff based on the Budyko framework. The catchment parameter n reflects all the factors that can affect the partition of precipitation into evaporation or runoff (Roderick & Farquhar, 2011). It includes topography, soil characteristics, geologic characteristics, vegetation, land cover, and climatic factors (precipitation seasonality, intensity and spatial distribution etc.) (Roderick & Farquhar, 2011; D. Yang et al., 2007; H. Yang et al., 2008; L. Zhang et al., 2001). Although geology, topography and soils are not likely to experience any large scale changes in the time considered in this study, the catchment characteristic of n itself may change in the future due to land cover change (Li et al., 2013) and vegetation change (Porporato, Daly, & Rodriguez‐Iturbe, 2004; D. Yang et al., 2009) increased CO2 (Gedney et al., 2006), those changes in the catchment characteristics are out of the scope of this study since the compared global hydrologic models also assume constant land and vegetation covers.

Most of the literature, quantifies the projections of $Q$ using the sensitivity framework of Roderick and Farquhar (2011) introduced in the Appendix. This sensitivity framework uses a Taylor approximation to solve the differential equations which results in errors quantified in H. Yang et al. (2014). Since the dataset allows to directly use the MCY equation to find *E* and *Q* we avoid the error of the sensitivity framework by doing the calculation directly. In the rest of the chapter the MCY equation is referred to as the Budyko equation.

### *4.2.3. Metrics of performance*

In order to test the performance of the projections from the Budyko equation with respect to the model projection we calculated the squared correlation coefficient $r^2$, coefficient of determination $R^2$, and the median error ME. These metrics are calculated as:

$$r^2 = \frac{\left(\sum_{i=1}^{n}\left(Q_{Bi} - \overline{Q_B}\right)\left(Q_{Mi} - Q_M\right)\right)^2}{\sum_{i=1}^{n}\left(Q_{Bi} - \overline{Q_B}\right)^2 \sum_{i}^{n}\left(Q_M - \overline{Q_M}\right)^2} \qquad (4\text{-}4)$$

where $Q_{Bi}$ and $Q_{Mi}$ are the runoff projected by Budyko and the model respectively for any given case *i*, and *n* is the total number of cases (35 basins x 3 GCMs x 2 scenarios = 210).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Q_{Bi} - Q_{Mi})^2}{\sum_{i=1}^{n}\left(Q_{Mi} - \overline{Q_M}\right)^2} \qquad (4\text{-}5)$$

$$ME = median\left(\frac{Q_{Bi} - Q_{Mi}}{Q_{Mi}}\right) \qquad (4\text{-}6)$$

### *4.2.4. Mann-Whitney Test for significance*

To test for significant changes in runoff and other variables for each basin we used the non-parametric statistical test of Mann-Whitney. The test posts the null hypothesis that $\mu X = \mu Y$, where $\mu$ represents the means of the series X and Y. The test unifies both series as one and ranks them. The test statistic is defined as follows:

$$M_w = \sum_{i=1}^{n_X} R_i \tag{4-7}$$

where $R_i$ is the rank of each value of series X or Y. Critical values of the test statistic are provided in Von Storch and Zwiers (2001).

### 4.3. Results of the comparison

*Figure 4-1* shows the comparison of runoff in the future period projected by global hydrologic models and the Budyko equation. The grey shades in the figure illustrate the ranges of discrepancy corresponding to ±20%, ±10%, and ±5% between projections by the two approaches. The figure indicates that 95% of the 210 total cases (35 river basins x 3 GCMs x 2 Scenarios) are within ±20% of the error, 70% of the cases are within ±10%, and 38% are within ±5% (Table 4-2). To quantify the overall performance, Table 4-3 also displays the squared correlation coefficient $r^2$ and the coefficient of determination $R^2$. Furthermore, to make the figure more visible with individual river basin names, Table 4-2 presents the same results but only from outputs of a single GCM (CNRM GCM) under A2 scenario.

It is obvious that the magnitude of projected future runoff differs significantly depending on the climatic zones. According to the statistics summarized in Table 4-3, Humid Tropic (HT) region has the best performance ($r^2 = 0.993$, $R^2 = 0.986$), followed by Dry region ($r^2 = 0.956$, $R^2 = 0.931$). On the other hand, Temperate (Temp) and Subarctic (SA) regions show comparatively low performance ($r^2 = 0.760$, $R^2 = 0.724$; $r^2 = 0.919$, $R^2 = 0.599$ respectively).

For further understanding of the Budyko performance, the relative changes of runoff from the present period (1960-2000) to the future period (2060-2100) were calculated. Table 4-3 shows the results of the relative changes of runoff projected by the two approaches with the identifications of significant or non-significant changes in runoff. The significance of the changes in runoff was determined using the Mann-Whitney test (Von Storch & Zwiers, 2001) with a 5% confidence level. The figure suggests that in the HT region, about 56% of the cases show significant changes (Table 4-4) and the majority of changes are increases in runoff in the future. In this region, Budyko consistently underestimates future runoff (ME = -0.042).

*Figure 4-2* shows that the SA region has the highest number of cases with significant runoff changes (86%; Table 4-4). In addition, both the hydrologic model and the Budyko equation suggest increases in runoff. The relative runoff change in *Figure 4-2* clearly shows that the Budyko equation consistently overestimates the future runoff as compared to the models in this region. The overestimation by the Budyko equation can be also confirmed in *Figure 4-3*, which shows the distributions of the relative errors and their mean values (ME = 0.110).

The Temp and Dry regions have lower median errors (ME = -0.008 and ME = -0.019); however, this is due to the compensation of large positive and negative errors. In these regions, the ranges of the relative errors are larger than in HT and SA regions as shown in *Figure 4-3*.

## 4.4. Patterns of changes in runoff: the contribution of storage and seasonality

As described in the previous section, unique characteristics in the performance of the Budyko projections were found. In this section, the possible reasons for the different performance in different climatic regions with respect to the seasonality of water and energy availability, and hydrologic storage changes are discussed.

### *4.4.1. Humid Tropics*

In the HT region, most of the basins showed increases in runoff by both methods, which were underestimated by the Budyko equation. *Figure 4-4* Point *a* displays the present and future climatology of $P$, $E$, $Q$, and $E_P$ at the Ganges River basin as an example. The main characteristic of the basins in this region are energy limited in the wet season and the excess rainfall becomes runoff with temporal water storage in the basin. According to the GHM, runoff ratio ($Q/P$) in the present condition is 0.543. Note that in this study, $Q/P$ by the Budyko equation becomes the same as the one by hydrologic model for the present climate condition because the parameter $n$ was estimated based on the output of the hydrologic model. On the other hand, for the future climate condition, estimated $Q/P$ will be higher by the model (0.646) than the Budyko equation (0.616). To find out the reason why the $Q/P$ increases more by the hydrologic model, we analyzed how different storage components contribute to runoff. To quantify the contribution ratio, the CCR introduced by Kim et al. (2009) was used (see Appendix). According to the CCR, we found that soil moisture and surface storage dominate the runoff in this basin. In terms of their changes, the CCR of surfaces storage increases from 39% to 46%, while that of soil moisture decreases from 54% to 50%. Hence the process based hydrologic model suggests more contribution from quick response-type surface runoff as the soil moisture storage approaches an upper limit with the increase of precipitation in the future (Milly, 1994). On the contrary, the constant $n$ parameter in the Budyko equation assumes no change in the runoff generating mechanism. As a result, the Budyko equation comparatively underestimates the increase of the future runoff.

### *4.4.2. Subarctic Arctic*

In the SA region, all of the basins also showed increases in runoff, but they were overestimated by the Budyko equation. As an example, *Figure 4-4* displays the present and future climatology of $P$, $E$, $Q$, and $E_P$ at the Yenisei River basin. The main characteristic of the basins in this region are water limited in summer and the seasonality of water and energy availability are in phase. From the figure, it can be seen that both E and Q are increased by the increase in P. However, the difference lies in how it is partitioned in the future. Budyko projects a partition of $E/P$=0.424 and $Q/P$=0.576. The partition projected by Budyko only considers changes at mean annual scale, therefore ignoring the effects of seasonality. On the other hand, the model is able to take into account the seasonal differences in water and energy balances. Since the basins in the SA region are water limited during spring and summer periods (March-September), the model partitions more precipitation into evaporation than Budyko. The model partitions $E/P$=0.458 and $Q/P$=0.509, therefore projecting less change in the partition especially in runoff.

### *4.4.3. Dry and Temperate regions*

Contrary to the HT and SA regions, there is no apparent pattern that defines the behavior of the Budyko projections with respect to the model. According to basin by basin inspection (*Figure 4-5* as a selected example), seasonality of water and energy availability affect over- or under- estimations by the Budyko equation. Basically basins with in phase of $P$ and $E_P$ showed the similar behavior as the SA region (i.e., overestimation), out of phase basins show similar behavior as the HT region (i.e. underestimation). Nevertheless, for basins in Dry and Temp regions, further assessment is required to understand the characteristics of runoff projections by the Budyko equation. The patterns were also more complex in the two regions because the projected climate change shows more diverse patterns in those basins.

### *4.4.4. Basins without significant changes in runoff but significant changes in precipitation*

There are several basins that are projected to experience increases or decreases in precipitation without significant changes in runoff according to the modeled data. In these cases, the Budyko equation readjusts the basin to the new water availability causing larger errors in small change basins. Some of the cases include projections from Budyko equation and the GHM with different sign (i.e. Budyko equation increases runoff but the model decreases it or vice versa). From these cases, it is noted that the phasing of the change is reliant on the projection in the case of the model. This happens because while total precipitation decreases, there is an increase during the winter months, at which runoff can be generated. Budyko only accounts for total precipitation, hence the projection decreases. The opposite case happens if a total increase in precipitation with the increase happens during summer with a slight decrease in winter. This further exemplifies how the sensitivity of runoff can be dependent to seasonality and to the timing of changes.

### *4.4.5. Particularities in the comparison due to the LPJmL model structure*

The Lund-Potsdam-Jena managed Land (LPJmL) model features the dynamic global vegetation model (DGVM), designed to simulate the carbon and vegetation patterns with the components to simulate the state variables and fluxes in the land atmosphere interaction (Gerten et al., 2004; Rost et al., 2008). One of the main features of the model is that vegetation behavior reacts to the atmospheric forcing and land surface behavior in the attempt of creating more realistic simulations than stand-alone hydrological models (Gerten et al., 2004). Since vegetation dynamics is one of the dominating factors of the catchment characteristic parameter of the Budyko equation, some particularities in the LPJmL model can also be addressed as reasons for the departure of both methodologies to project into the future. The parameter $n$ in the Budyko equation has been found to be related to the vegetation characteristics of stomatal opening (Roderick & Farquhar, 2011), vegetation type (L. Zhang et al., 2001), and vegetation cover (Roderick & Farquhar, 2011; D. Yang et al., 2009). Additionally, other factors such as infiltration (D. Yang et al., 2007) are also related to vegetation type and cover and also affect the parameter $n$. Of these characteristics, stomatal opening is perhaps the feature that could have important implications in this comparison since the dynamical vegetation of LPJmL adapts to different climate conditions and to modified carbon levels influencing stomatal openings and plant outtake from soil moisture (Gerten et al., 2004). Roderick and Farquhar (2011) identified qualitatively that decreasing stomatal openings would decrease the parameter $n$, hence partitioning more water to runoff than to evaporation.

Gerten et al. (2004) analyzed how the increases in $CO_2$ would affect runoff generation globally. Their main findings were that runoff would increase dramatically in higher latitudes and in the wet tropics. Also, they found that in energy limited environments there was a reduction of transpiration due to increased carbon assimilation, decreasing water loss through stomata. In drier regions, transpiration is limited by water availability; hence the basins were not sensitive to carbon changes. The results from Gerten et al. (2004) consider doubling of the carbon content, which would be consistent with the A2 scenario used in this study, but it maintained the same climatic data. In the case of this study, only the climatic data changed. Despite this aspect, Gerten et al. (2004) found only a 5.5% present increase in runoff, consistent also with other studies (Hickler, Prentice, Smith, & Sykes, 2003). As it has been discussed, the model dramatically increases runoff in humid tropical basins which could be related to the underestimation by Budyko in this region. However, the model also increases dramatically the runoff in the subarctic, which is overestimated by Budyko, meaning that Budyko projects even higher changes.

Regarding a basin by basin analysis, also performed by Gerten et al. (2004) found that the model overestimates humid and dry basins (consistent also with Haddeland et al. (2011)) and underestimates high latitude basins. This can justify that the Budyko equation underestimations in the tropical basins and overestimations of Budyko equation in the subarctic region. Gerten et al. (2004) also found good agreement in basins of the temperate region like Mississippi and Danube where no particular behavior in the projections was found.

### 4.5. Concluding summary

This chapter compared future runoff projections by using a detailed, process based hydrological model and a simple Budyko equation for the 35 largest basins of the world by using the WDD and 21CMO described in Chapter 2. The obtained conclusions are summarized as follows:

- The future runoff projections by the two approaches agree with each other; 95% of the 210 total cases are within ±20% error, 70% of the cases are within ±10%, and 38% of the cases are within ±5%.
- In the HT region, Budyko underestimated the future runoff with ME = -0.042. With the increase of *P* in the future, *Q*/*P* also shows increasing patterns according to the hydrologic model due to more saturation, whose mechanism is not represented by the Budyko equation. This condition is summarized in *Figure 4-6* Point a.
- In the SA region, Budyko overestimated the future runoff with ME = 0.112. The basins in this region will also experience the increase of *P*, but the high seasonality of *P* and water limitation in the summer will partition more water towards *E* according to the hydrologic model. Those seasonalities are not considered by the Budyko equation, which results in the overestimation of the future runoff. This condition is summarized in *Figure 4-6*.
- Basins in the Dry and Temp regions showed larger discrepancy between the model and Budyko projections. Although the seasonality of *P* and $E_P$ seems to be an important factor for the underestimation or overestimation, there are many other possible reasons for the behavior, which requires further detailed investigation in these regions. The possible mechanisms of change in these regions are presented in *Figure 4-6* Point b for basins in phase and *Figure 4-6* Point c for basins out of phase.
- Additionally in the Dry and Temp region projections, contradicting directions were found. This is due to the timing of changes in water with respect to energy. Budyko can only account for the total annual change and project it according to its equation while the models are sensitive to this aspect, as discussed before.
- Particularities of the LPJmL model, especially the complex dynamic vegetation component can have particular implications in the representation of present climate and projections into the future. It is important to test the Budyko type equation with

the projections of other types of models were other behaviors can be identified and attributed to the different components and conceptualization of hydrological models. Additionally, it is also important to test the projections of the Budyko equation, not only with predetermined modeled data like in the present study, but with the freedom to modify parameters in models and assess how these changes relate to such projections.

*Table 4-1*

*Functional Forms of the Water Energy Balance*

| Id | Functional Form | Parameter | Reference |
|---|---|---|---|
| Screiber | $E = P[1 - \exp(-E_P / P)]$ | None | (Schreiber, 1904) |
| Ol'Dekop | $E = E_P \tanh(P / E_P)$ | None | (Ol'Dekop, 1911) |
| Pike | $E = P / \left[1 + (P / E_P)^2\right]^{0.5}$ | None | (Pike, 1964) |
| Budyko | $E = \left\{P\left[1 - \exp(-E_P / P)\right] \cdot E_P \tanh(P / E_P)\right\}^{0.5}$ | None | (Budyko, 1974) |
| Fu | $E = P\left[1 + \omega(E_P / P)\right] / \left[1 + \omega(E_P / P + P / E_P)\right]$ | ω | (B. Fu, 1981; L. Zhang et al., 2001) |
| Choudhury | $E = P / \left[1 + (P / E_P)^n\right]^{1/n}$ | *n* | (Choudhury, 1999; Mezentsev, 1955) |

*Note:* Based on H. Yang et al. (2008)

Table 4-2

*Number of Cases Within the Relative Errors (5%, 10%, 20%) by the Budyko Equation with Respect to the Model Projections.*

| | Relative Error | | |
|---|---|---|---|
| | 5% | 10% | 20% |
| All Cases (210) | 80 (38%) | 150 (71%) | 201 (95%) |
| HT (66) | 33 (50%) | 56 (85%) | 66 (100%) |
| Dry (48) | 14 (29%) | 29 (60) | 45 (94%) |
| Temp (54) | 23 (43%) | 41 (76%) | 50 (92%) |
| SA (42) | 10 (24%) | 24 (57%) | 40 (95%) |

Table 4-3

*Performance of the Projections by the Budyko Equation with Respect to the Model Projections.*

| All Cases | | | |
|---|---|---|---|
| Region | Metric | | |
| | $r^2$ | $R^2$ | ME |
| HT | 0.993 | 0.986 | -0.042 |
| Dry | 0.956 | 0.931 | -0.006 |
| Temp | 0.760 | 0.724 | -0.008 |
| SA | 0.919 | 0.599 | 0.110 |
| Total | 0.985 | 0.983 | 0.011 |

| CNRM A2 | | | |
|---|---|---|---|
| Region | Metric | | |
| | $r^2$ | $R^2$ | ME |
| HT | 0.997 | 0.991 | -0.042 |
| Dry | 0.965 | 0.927 | 0.042 |
| Temp | 0.961 | 0.959 | -0.008 |
| SA | 0.848 | 0.274 | 0.091 |
| Total | 0.996 | 0.995 | -0.007 |

Table 4-4

*Summary of Significant Change Assessment Using the Mann-Whitney Test.*

| Region | All Dataset | | CCNRM-A2 | |
|---|---|---|---|---|
| | Total No. Cases | Basins with Significant Change | Total No. Basins | Basins with Significant Change |
| All Cases | 210 | 132 (43%) | 35 | 25 (71%) |
| HT | 66 | 37 (56%) | 11 | 9 (82%) |
| Dry | 48 | 23 (48%) | 8 | 4 (50%) |
| Temp | 54 | 25 (46%) | 9 | 5 (56%) |
| SA | 42 | 36 (86%) | 7 | 7 (100%) |

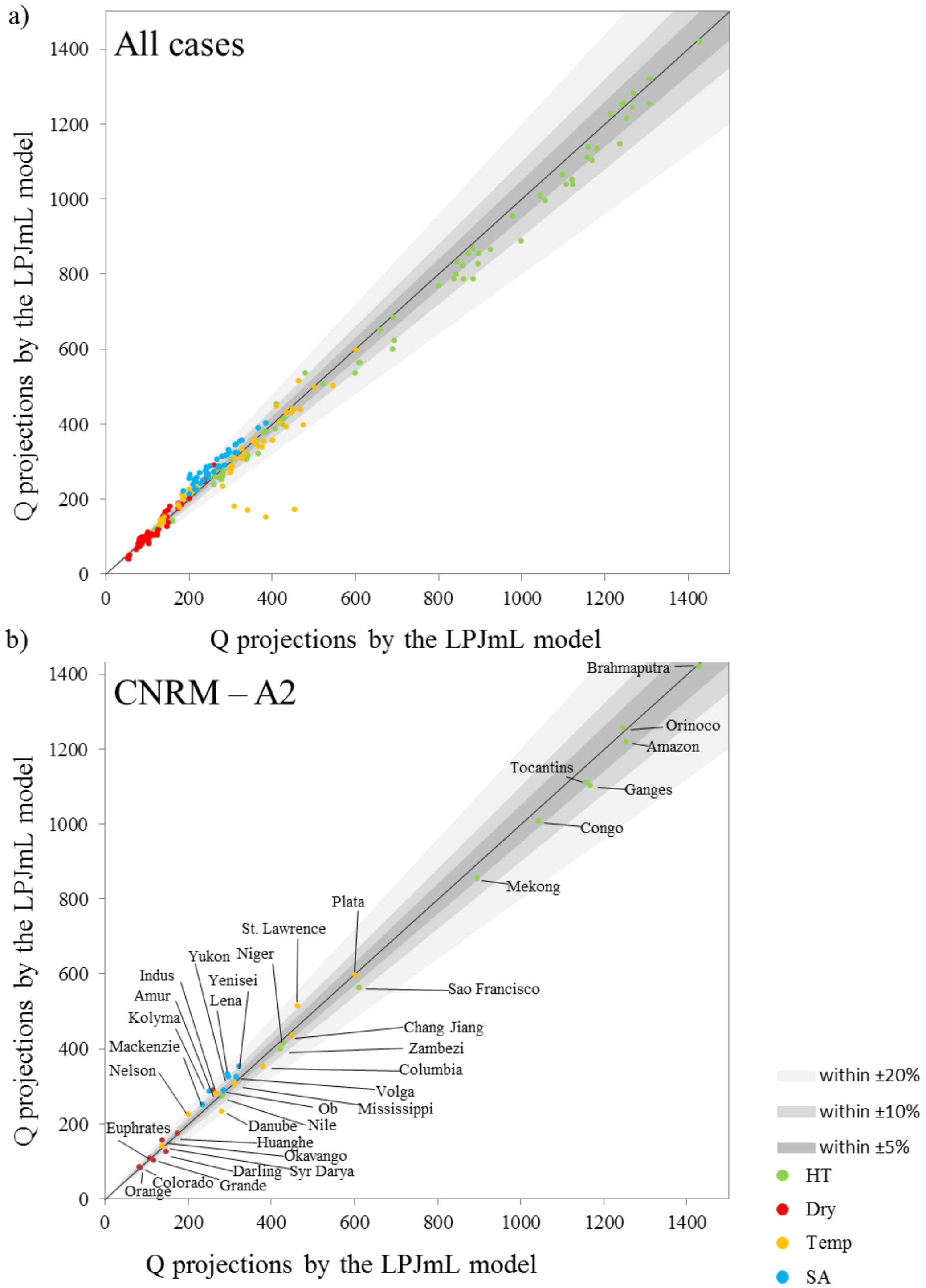



*Figure 4-1* Scatter plot of model projection and projections using the Budyko equation a) for all the cases within the dataset and b) using the projections driven by the CNRM GCM under A2 scenario conditions.

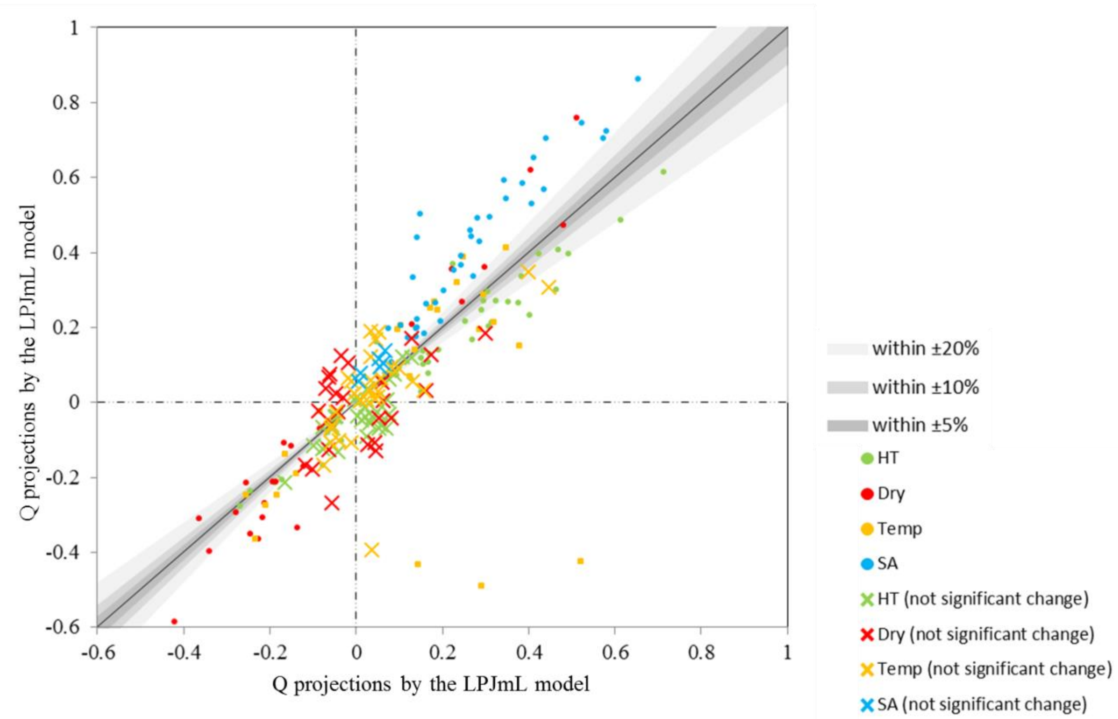



*Figure 4-2* Scatter plot of relative changes from model projection and projections using the Budyko equation a) for all the cases within the dataset and b) using the projections driven by the CNRM GCM under A2 scenario conditions.

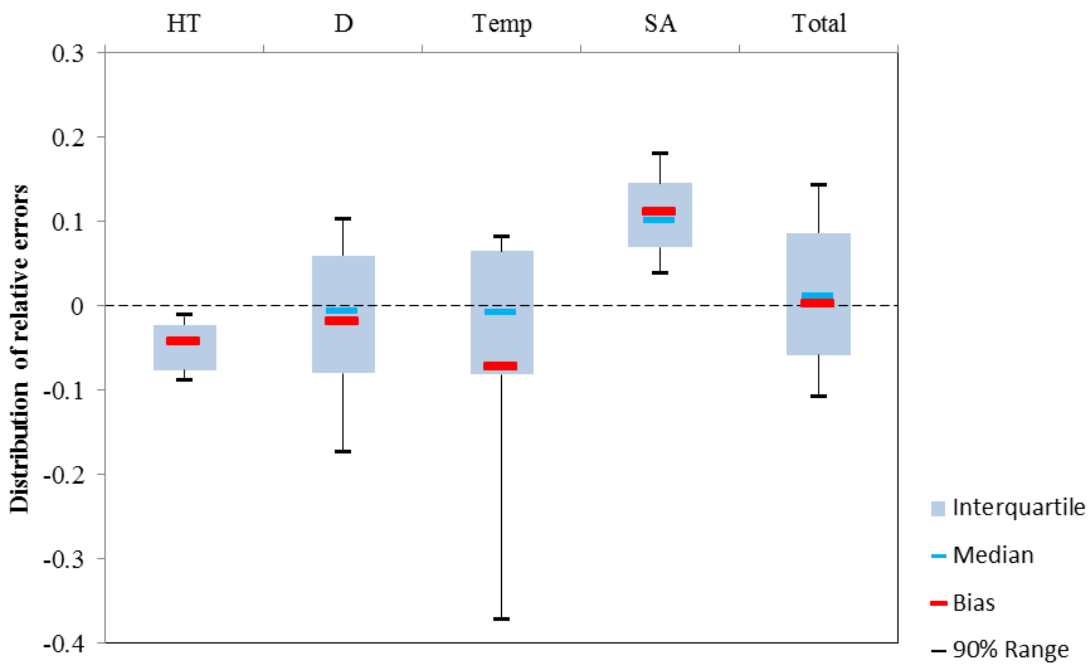
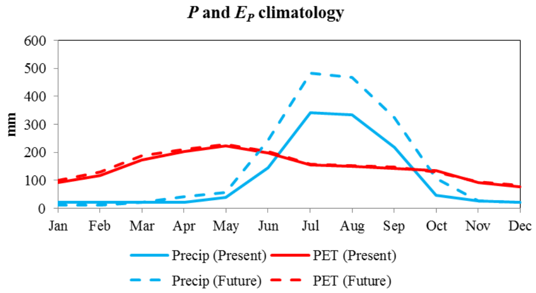
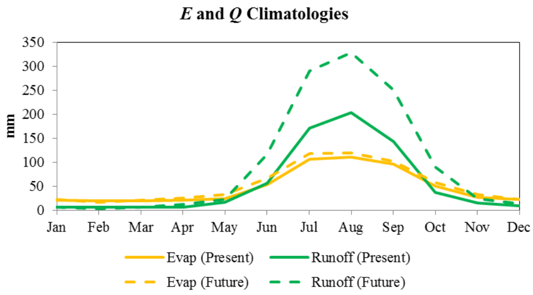



*Figure 4-3* Distribution of relative errors and Bias (Mean of relative errors) of projections using the Budyko equation with respect to the projections from the hydrological model calculated for basins with significant change only.

a) HT: Ganges



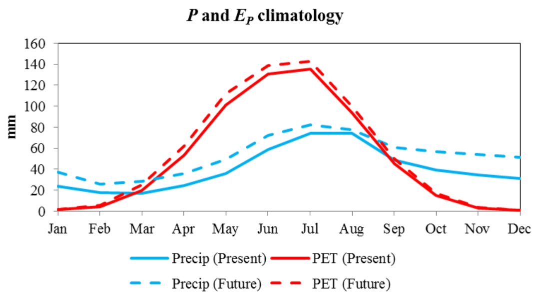

*Q/P*:

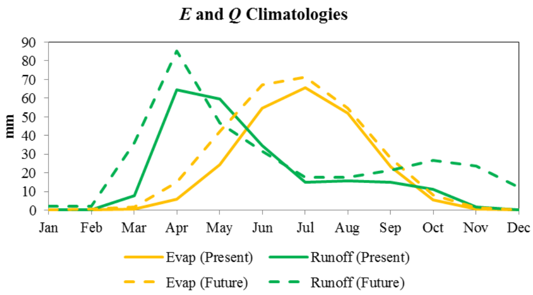
Present: 0.543
Future (Budyko) : 0.616
Future (Model): 0.646

*E/P*:

Present: 0.457
Future (Budyko) : 0.392
Future (Model): 0.353

b) SA: Yenisei




*Q/P*:

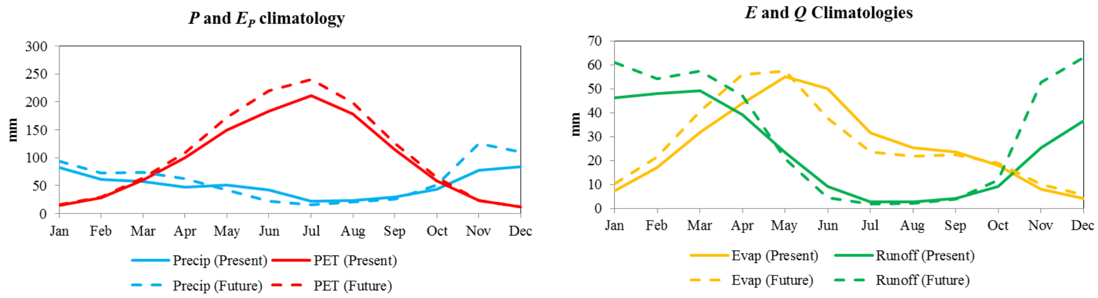
Present: 0.468
Future (Budyko) : 0.576
Future (Model): 0.509

*E/P*:

Present: 0.485
Future (Budyko) : 0.424
Future (Model): 0.458

*Figure 4-4* Example of projected changes in the Ganges River basin (in HT region) and in the Yenisei River basin (in SA region).

a) Out of Phase: Columbia




a) In Phase: Danube

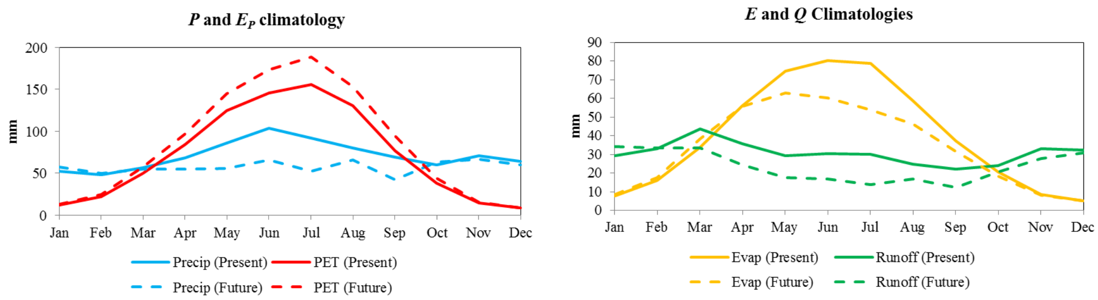



*Figure 4-5* Example of projected changes in the Columbia basin (Out of Phase) and in the Danube basin (In Phase) both in the Temp region.

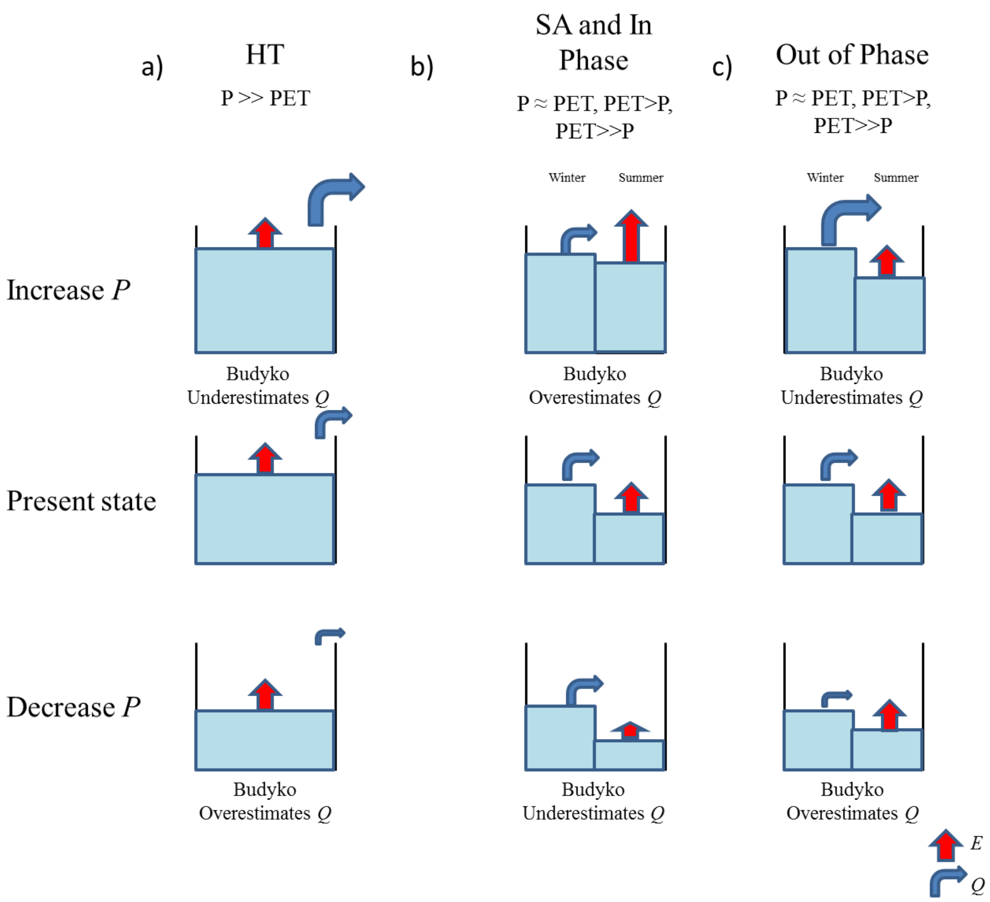



*Figure 4-6* Schematic summary of possible mechanistic changes in different regions and basin characteristics.

# 5. Conclusions and Policy Implications

The general objective of this thesis was to increase the understanding of how hydrologic functions are related in different climatologies, and how these functions change under future projections. By analyzing the temporal variations of precipitation, evaporation, runoff, and storage, hypotheses about the hydrologic functions in these different climatologies were derived. Particular relations of water and energy balances had an important impact on these hypotheses; therefore, it was decided to compare future climate change projections by using a simplified water-energy balance framework to hydrological models, and analyze how the models feature functional changes in the different climates. This chapter presents general conclusions of the thesis as detailed conclusions of each part are given in each chapter. In this study, the spatial average of the 35 largest river basins of the world was used with the global datasets of model outputs from the EUWATCH project.

## 5.1. Conclusions

The hydrological functions of river basins are characterized by the main hydrological variables of precipitation, evaporation, storage and runoff. The temporal characteristics of these variables and their propagation from variable to variable can be an indicator of the manner in which the hydrologic functions work in a basin. To achieve the objective of determining the present hydrologic functionality of different river basins a sub objective of deriving a classification using a simple measure was pursued. The concept of recurrence was introduced as the degree to which a monthly hydrological variable returns to the same state in subsequent years. It was found that the relation and effect of hydrological variables is greatly affected by seasonality, aridity and the phasing of water and energy balances. Of particular importance, it was found that the recurrence in runoff is greatly affected as aridity increases and evaporation represents a greater component of the water balance in a basin. Additionally, in regions such as the temperate area and the subarctic, storage dominates the temporal characteristics of runoff, but the amount of precipitation determines that these characteristics are maintained. This component of the thesis emphasized previous knowledge about aridity, seasonality and phasing as important aspects to account for in water management for the timing and amount of water available through runoff but also gave new insights on their relation to the interannual variability of the cyclical yearly pattern. Additionally it was possible to some degree, to identify a regionalization in the patterns of recurrence.

For simplicity, the main results were shown using a single model; however, the analysis was performed using four LSMs and four GHMs. Consistency in the classification and behavior of the patterns of recurrence was found in most of the models. Several outliers were found in particular types of basins but it was possible to attribute the different behavior to a particular feature within the different model. The methodology could be improved if a dataset based on observations is used instead that a modeled dataset.

An important implication of recurrence is that it can be an indicator of inter- and intra- annual variability. It is also an indicator of the behavior of an extreme value distribution, as less recurrent variables are likely to have steeper distributions. Less recurrent variables are also likely to have less predictability than recurrent variables.

The second general objective of the thesis was to evaluate how the hydrologic functions react to changes from climate. Since the relations of energy and water availability proved to be important drivers of the hydrologic functionality of basins, it was decided to compare future climate change projections from a framework that relates these balances but ignores the hydrologic functionality (Budyko framework), to hydrological modelling. Hydrological modelling also related water and energy balances and allowed for analysis of the functionality of basins. It was found that in general terms, the two approaches agree well; however, the performance varies from region to region. It was found that in the HT region, Budyko underestimates runoff, although it has higher agreement. In the SA region it was found that Budyko overestimates runoff and has larger errors. The dry and temperate regions have larger errors and the performance is quite complex due to the changes also being complex. From the comparison it was found that the models are able to represent changes in seasonality and storage that Budyko is notable to do. Three different behaviors of change were found mainly showing adjustment in the storage components of basins further influencing the behavior of runoff.

It is important to highlight that these component was carried out with only one model that has particular characteristics, specially a dynamic vegetation module. This aspect has particular implications on how the model simulates the present state of basins and projects into the future. It is important to expand a comparison to models that have different types of modules and conceptualizations to test how Budyko performs with respect to these other model characteristics. Additionally, it would be important to use a hydrological model, and modify its parameterizations to analyze the behavior of Budyko to known modifications, instead of using a predetermined dataset.

### 5.2. Limitations

Undertaking the task of analyzing the hydrologic functions and particularly the behavior of storage characteristics is highly complex. In order to carry out the analysis performed in this study several assumptions and simplifications were made. The dataset used also has several assumptions. Vegetation has a great effect on hydrology as it influences evaporation and effective rainfall through interception and throughfall processes. If vegetation changes the hydrological processes are also modified. However, in this study it is assumed that vegetation cover and type does not change. Additionally, the characteristics of vegetation are not included to derive the hydrologic functions' behavior.

Aside from the emission scenarios used through the GCMs to derive the datasets this study does not consider the impacts of humans on hydrological processes because the dataset considers naturalized conditions. Humans impact hydrology by extracting water for several uses such as agriculture, industry, and energy generation among others, and by building hydraulic infrastructures such as reservoirs or diversion channels. Additionally, they have other effects by modifying landscape through mining, road construction, agricultural terracing, and other land cover changes. All these aspects modify runoff processes by changing runoff coefficients, infiltration coefficients and evaporation. The impacts of humans on the hydrological cycle will increase as the human population continues to increase. It is also important to consider that the human system, the hydrological system, and the climate system give feedback to each other. This issue calls for multidisciplinary studies for our understanding to become each time more holistic.

Another limitation of this study is the scale selected. Following a top-down approach, a large river basin scale was selected. With this approach, general processes were identified, but at smaller scale, more specific processes have a more important role. Large scale studies are important, but it is also important to bring the concepts acquired at this scale to smaller scales and vice versa. Additionally large basins are heterogenic in geology, topography and land cover, making it necessary to downscale these large studies into smaller areas at which specific impacts can be tested. From any study of hydrological classifications, there are always existing exceptions, which are proof of other aspects that affect the hydrological processes of basins.

This study used a multimodel dataset which can have large uncertainties due to the limitation in the representation of processes in models. There are other data sets, that also have large uncertainties but that can prove complementary to this study. There are reanalysis, remotely sensed, and gridded datasets derived from observations that can be used and compared to the results with the current dataset. All of these datasets including the ones used in the current study will be improved in the future with the increase in knowledge and technology, making it possible to improve conceptualizations.

### 5.3. Future Work and policy implications

One of the issues to highlight from the current study is the aspect that recurrence can be an important measure for water managers and policy makers. It is of high importance for such professionals to understand the degree of confidence that they can have upon the "typical" yearly pattern of available water in a given basin. It is also important to know how this property can change in the future and whether the recurrence of a variable can decrease in the future.

If the classification presented in this study can be further downscaled, it might be interesting to analyze how the different patterns in sub basins create a general pattern in the complete large basin. This information can help policy makers and water managers to identify important regions in basins that require more attention for preservation.

As with any other classification, the final goal is to have a transferability of concepts among subjects of similar classes, in this case of basins. If transferability of concepts is achieved, transferability of actions can also be possible. Additionally, since basins are dynamical systems under constant change, different classes are examples of different conditions and can be an indicator of the future of present basins under a given change.

Information about runoff sensitivity can be an important indicator of future water availability. Runoff sensitivity is defined as the relative changes of runoff with respect to relative changes in precipitation. However, we know that according to the hydrologic functions, the sensitivity of runoff is not necessarily related directly to precipitation. It is important to assess the sensitivity of evaporation and storage components to precipitation, and the sensitivity of runoff to storage. The final goal should be to derive a function of the sensitivity of runoff with respect to precipitation but take into account the characteristics of storage and effects of energy. This has important policy implications, as the policies regarding water have to be developed accounting for future runoff conditions.

An important aspect highlighted from this study is the recurrence of hydrological variables. Seasonality and aridity are important factors to which humans have adapted over years of interaction. For example, cultures that developed in dry areas have particular adjustments to those conditions. The patterns of recurrence should also be included as an important metric of variable characteristics, especially in runoff. The recurrent pattern of runoff will be an indicator of how variable the availability of water is and how this indicator will change in the future.

Most important is to eventually involve human impacts into hydrological assessments. Understanding the natural hydrological system is important, but human activity is more incidental every day. Measures for water use, disaster prevention and resource preservation have to be related to hydrologic functioning but most importantly, the study of hydrologic functioning has to relate to human interference. This task is not only important but is also an enormous challenge due to the complexity of societal growth and the uncertainties of population projections and economic development.

Gaining an understanding of the different properties of basins and how they can change might make it possible to study the resilience of current states of basins and therefore be able to know the effects that particular pressures can have on basin functionality and the amount of pressure to which basins can be subjected.

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Appendix A

**Storage properties metrics**

The metric used in this study to analyse the storage contribution is the *CCR* originally proposed by (Kim et al., 2009). The *CCR* of each component is given by:

$$CCR_S = \frac{MAD_S}{TV} \tag{A1}$$

where $MAD_S$ is the mean absolute deviation of each component given by:

$$\frac{1}{N}\sum_{t}^{N}\left|S_t - \overline{S}\right| \tag{A2}$$

In Eq. A2, $N$ is the number of months, $S_t$ is the storage at month t, and $\overline{S}$ is the average of the storage component. *TV* in Eq. A3 represents the total variability of storage and is equal to the summation of *MAD* of each component:

$$TV = \sum_{S}^{Storages} MAD_S \tag{A3}$$

**Sensitivity framework based on the MCY functional form of the Budyko equation.**

This section introduces the methodology derived by Roderick and Farquhar (2011).

From equation 4.3, the sensitivity of $E$ to changes in $P$, $E_P$, and $n$ is deriver as follows:

$$dE = \frac{\partial E}{\partial P}dP + \frac{\partial E}{\partial E_P}dE_P + \frac{\partial E}{\partial n}dn \tag{A4}$$

The partial differentials of equation A4 are described as the sensitivity coefficients and are given as follows:

$$\frac{\partial E}{\partial P} = \frac{E}{P}\left(\frac{E_P^n}{P^n + E_P^n}\right) \qquad \text{(A5)}$$

$$\frac{\partial E}{\partial E_P} = \frac{E}{E_P}\left(\frac{P_P^n}{P^n + E_P^n}\right) \qquad \text{(A6)}$$

$$\frac{\partial E}{\partial n} = \frac{E}{n}\left(\frac{\ln\left(P^n + E_P^n\right)}{n} - \frac{\left(P^n \ln P + E_P^n \ln E_P\right)}{P^n + E_P^n}\right) \qquad \text{(A7)}$$

This sensitivity framework assumes steady state, meaning that it considers any change in storage negligible. Using the water balance concept introduced in Equation 1.3, the sensitivity of runoff is given as follows:

$$dQ = dP - dE \qquad \text{(A8)}$$

Combining A4 and A8 the sensitivity of runoff becomes:

$$dQ = \left(1 - \frac{\partial E}{\partial P}\right)dP - \frac{\partial E}{\partial E_P}dE_P - \frac{\partial E}{\partial n}dn \qquad \text{(A9)}$$

Further, the relative changes in runoff

$$\frac{dQ}{Q} = \left[\frac{P}{Q}\left(1 - \frac{\partial E}{\partial P}\right)\right]\frac{dP}{P} - \left[\frac{E_P}{Q}\frac{\partial E}{\partial E_P}\right]\frac{dE_P}{E_P} - \left[\frac{n}{Q}\frac{\partial E}{\partial n}\right]\frac{dn}{n} \qquad \text{(A10)}$$

This framework uses an first order approximation of the Taylor expansion to obtain the differentials that give the sensitivity coefficients (H. Yang et al., 2014). H. Yang et al. (2014) calculated the higher orders of the Taylor expansion and calculated the possible errors of using Roderick's framework directly. Since the dataset employed in this study allows the calculation of the changes in $E$ and $Q$, directly from the changes of $P$ and $E_P$, without calculating the sensitivity coefficients, Roderick's framework is not used.

Table A1

*Summary of Class Characteristics from the classification using recurrence.*

| Class | Basins | Region | Characteristics | Observations |
|---|---|---|---|---|
| QPES | Amazon, Brahmaputra, Changjiang, Ganges, Mekong, Niger, Nile, Yenisei | Tropics, Subtropics (Asian Monsoon), and Subarctic (Central Eurasia) | Tropical and Subtropical Humid Basins<br>Snow dominated basins with high recurrence in precipitation and high precipitation during winter | Variables follow the same pattern as precipitation fills storage and storage further supplies runoff and evaporation in an equally recurrent pattern |
| QPE | Lena, Mackenzie | Subarctic (West Eurasia and Central North America) | Snow dominated basins with small precipitation in winter | *P* is recurrent but concentrated in summer, winter snow volume is not high enough to make storage recurrent. However the amount of snow does generate a recurrent pattern in runoff |
| QPS | Orinoco | Tropics | Equatorial basin with highly constant evaporation pattern | *P*, *S*, and *Q* have a recurrent pattern but the constant high water and low energy supplies result in a low recurrence pattern in evaporation |
| QES | Ob, Volga | Subarctic (Central Asia) | Snow dominated basins with low recurrence in precipitation, water limited in summer, and high precipitation during winter | Important amount of precipitation during winter creates a large snow volume which creates a recurrent runoff pattern regardless of the low recurrence in precipitation |

| | | | | |
|---|---|---|---|---|
| QE | Yukon | Subarctic (Alaska) | Snow dominated basin with low recurrence in precipitation, water limited in summer and rather low precipitation in winter | Low $P$ in winter does not allow a recurrent pattern in storage because of low snow volume; however, $Q$ is recurrent |
| PES | Tocantins, Zambezi | Tropics (Southern South America and Africa), Temperate (East Eurasian Continent affected by Oceanic atmospheric flow) | Tropical humid basins with $E_P$ peaks at different time as $P$ | Desynchronization of the $P$ and $E_P$ cycles allows for filling of storage and also emptying during rainy and dry seasons, respectively. $Q$ is only generated for extreme precipitation due to lack of saturation in $S$. |
| PE | Amur, Congo, Huang He, Okavango, Plata | | Basins with high evaporative index (0.7-0.8) with $E_P$ peaking at the same time as $P$ | Runoff generation and storage change are highly limited by $E$ due to the synchronization of $P$ and $E_P$. |
| ES | Columbia, Euphrates, Mississippi, Syr Darya | Temperate (North America, Europe and Central Asia) South America | Mid-latitude basins with important amount of precipitation in winter, some influence of snow, and water limited in summer | $S$ increases during winter regardless of the $P$ pattern, however snow volume is not such as to pass the pattern onto $Q$. |

| | | | | |
|---|---|---|---|---|
| E | Danube, Indus, Kolyma, Nelson, Sao Francisco, St. Lawrence | Temperate (North America, Europe and Central Asia) South America | Winter storage dominated basins due to the presence of snow with low storage fluctuations Tropical basin with no recurrent patterns in precipitation but water availability restrained to one particular season only | Irregular or low *P* patterns transmit directly on to other variables, but *E* is recurrent due to the seasonal availability of energy. |
| L | Colorado, Darling, Grande, Orange | Subtropics (Desert Belt) | Arid basins | Irregular *P* transmits to other variables as isolated events are the only water available for any hydrological process to take place |