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Discussions

Hydrological recurrence as a measure for large river basin classification and process understanding

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Abstract

Hydrologic functions of river basins are summarized as water collection, storage and discharge, which can be characterized by the dynamics of hydrological variables including precipitation, evaporation, storage and runoff. In some situations these four variables behave more in a recurrent manner by repeating in a similar range year after year or in other situations they exhibit more randomness with higher variations year by year. The degree of recurrence in runoff is important not only for water resources management but also for hydrologic process understandings, especially in terms of how the other three variables determine the degree of recurrence in runoff. The main objective of this paper is to propose a simple hydrologic classification framework applicable to global scale and large basins based on the combinations of recurrence in the four variables. We evaluate it by Lagged Autocorrelation, Fast Fourier Transforms and Colwell's Indices of variables obtained from EU-WATCH dataset composed by eight hydrologic and land surface model outputs. By setting a threshold to define high or low recurrence in the four variables, we classify each river basin into 16 possible classes.

The overview of recurrence patterns at global scale suggested that precipitation is recurrent mainly in the humid tropics, Asian Monsoon area and part of higher latitudes with oceanic influence. 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 three variables. According to the river basin classification 10 out of the 16 possible classes were present in the 35 largest river basins in the world. In humid tropic region, the basins belong to a class with high recurrence in all the variables, while in subtropical region many of the river basins have low recurrence. In 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 region, the amount of snow also influences the classes; more

snow yields higher recurrence in storage and runoff. Our 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 datasets to provide useful insights into the understanding of hydrologic regimes based on the classification.

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 cause for temporal variations in the land surface and atmosphere. Variations at seasonal scale are the most recognized patterns in most hydrological processes playing 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 at river basins.

The importance of storage dynamics has been highlighted with emerging new concepts in watershed hydrology. Fill and Spill (Spence and Woo, 2003; Tromp-van Meerveld and McDonnell, 2006; Shaw et al., 2012), connectivity (McGlynn et al., 2013) and threshold (Fu et al., 2013; Ali et al., 2013) are few examples amongst 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 et al., 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 and McDonnell, 2009), which ultimately influence on the sensitivity of the system to climate change (Tague and Peng, 2013). Hence storage dynamics should be incorporated as a fundamental metric for catchment classifications and comparisons (Wagener et al., 2007; McNamara et al., 2011).

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 evapotranspiration 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 et al., 2012). Coopersmith et al. (2012) derived the classification using the aridity index, seasonality, 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 before and after 1970, 1975 and 1980 (Coopersmith et al., 2014).

For global scale, several studies have also assessed the interaction of storage variables by using global circulation models. 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 and 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 and Dunne, 2002) and their influence on river discharge have been also analyzed using observed data and GCMs (Milly and Wetherald, 2002). Most literature in this regard has extensively focused on analyzing interactions and influences between the land surface and the atmosphere but hydrological classifications based on multi variable interactions have not been yet derived due to most existing classification's use of flow characteristics or climate regionalization only (Olden et al., 2012).

The objective of the study is to propose a classification framework at large river basins employing the temporal patterns in precipitation, evapotranspiration, storage and runoff utilizing a global dataset. We follow the framework of Jothityangkoon and Sivapalan (2009) 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 direct application of the concept is restricted because of intrinsic heterogeneity in large river basins. For example, complete saturation in an actual river basin does not take place or uniform field capacity cannot be defined as a threshold for runoff generation. Large river basins will not reflect the simplified idea of the thresholds but they also follow the theoretical framework and the behavior of filling and emptying to balance inflows and outflows. Hence it is more practical to directly analyze temporal patterns without defining hypothetical thresholds in the four variables. In particular we propose to analyze the similarity of the patterns of hydrological variables from one year to other years to classify river basins. We introduce the term of hydrological recurrence as the degree to which a monthly cycle repeats year after year. With the different degree of recurrence in the different variables we intend to group basins with similar characteristics.

For this objective we use data from the Water Model Intercomparison Project (WaterMIP) from the EU-WATCH (Water and Change) project. We start the analysis at a global scale analyzing each variable separately intending to unveil the geographical relations on recurrence for the different variables. Afterwards we include the 35 largest river basins in the world (basins larger than 600 000 km^2) and perform the analysis using the spatial average from each variable. We derived the classification depending on the different combinations that were found in the recurrence of hydrological variables. In order to explain the differences between classes and analyze how the recurrence of runoff is affected by and related to the recurrence in precipitation, evaporation and storage, a comparison of various hydrological processes (variable climatologies, potential evapotranspiration climatology, storage components climatology, and ratios to precipitation) was performed.

2 Data

For this study we selected to use the “WATCH 20th Century Model Output” from the WaterMIP datasets provided by EU-WATCH. This data set represents contemporary naturalized conditions, with no human interaction such as reservoirs or agricultural withdrawals at 0.5° spatial resolution (Haddeland et al., 2011). The selected data set provides the variables of evaporation and runoff (surface and subsurface); the storage components; and potential evaporation for some of the models. Storage components and the modules for precipitation input and calculation of potential evapotranspiration and generated runoff vary depending on the model (summarized in Table 1). River discharge is also provided for particular models but for comparative purposes generated runoff from land surface is selected. Precipitation is provided as a part of the WATCH Forcing Data for the 20th century (WFD). The forcing data are based on the European Centre for Medium Range Weather Forecasting (ECMWF) "ERA-40" reanalysis data (Weedon et al., 2010, 2011). The EU-WATCH project distinguishes LSMs and GHMs depending on a models solving energy balance equation or not.

LSMs require input rainfall and snowfall independently, which is provided by WFD dataset; whereas GHMs use their own algorithms to separate rainfall and snowfall, using total precipitation as input. The partitions within the GHMs are not available in the provided EU-WATCH dataset. Due to the data availability and simplicity for the global scale river basin classification, we analyze the total precipitation as the aggregation of rainfall and snowfall. Evapotranspiration, runoff and storage are also integrated as total because the element fluxes and storages are defined differently depending on the models.

The time period selected for the analysis is from 1979–2001 at a monthly scale. The original data including precipitation, evapotranspiration, storage and runoff was first analyzed to test their recurrences explained in the next section on the grid-cell basis, then they are averaged at the world's largest 35 river basins (Fig. 1) for the basin classification. The basins included are basins with area larger than 600 000 km^2.

3 Methods

3.1 Quantifying recurrence

This section introduces three metrics typically used for evaluating periodicity, which include autocorrelation (AC), Fast Fourier Transforms (FFT) and Colwell Index of Contingency (Colwell, 1974). The definitions are described below and their characteristics are discussed in Sect. 5.2.

3.1.1 Lagged autocorrelation (AC)

A serial autocorrelation (AC) defined as Eq. (1) describes the correlation of a time series with time lag k:

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

where r_k is the AC coefficient for lag k, N is the total number of observations, and $\bar{x}$ is the sample 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 bias 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:

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

For the recurrence measure with monthly time series, evaluating the AC of time lag only 12 is insufficient because it would only take into account the recurrence in contiguous years. We find 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.

3.1.2 Fast Fourier Transforms (FFT)

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

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

where m_τ is the harmonically fitted mean, μ 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 calculates as:

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

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

The intensity can be calculated from these parameters as:

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

The 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). This intensity is sensitive to the amplitude and magnitude of the time series, therefore to be able to compare different variables and basins, we applied a standard normalization.

3.1.3 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 and Sweeney, 1980), variations in flow velocity (Riddell and Leggett, 1981), rainfall distribution at a yearly basis (Miller, 1984), periodicity analysis in streamflow or rainfall data (Gan et al., 1991), classification of flow regimes for environmental flow assessments (Zhang et al., 2012), and description of waterholes in hydrological regimes (Webb et al., 2012). Colwell (1974) defined predictability as the measure of the certainty of knowing a state at a given time, being 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 the Colwell's Index requires first 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, whose ranges are between minus four to plus four, which is equally divided into 16 categories with intervals of 0.5σ.

Now let N_{ij} be the number of times that a variable falls in state i at time step j. Sum of all columns for each state i is X_i, 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:

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

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

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

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

$$H(XY) = -\sum_i \sum_j \frac{N_{ij}}{Z} \log \frac{Nij}{Z}. \tag{10}$$

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. Hence the contingency represents the degree of recurrence. For reference, the Constancy (C) and Predictability (P) are defined as:

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

$$P = 1 - \frac{H(XY) - H(X)}{\log s}. \tag{12}$$

3.2 Hydrological 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. 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. Figure 2 shows the classification tree, which results in a total of 16 possible classes depending on the combinations of high/low recurrence with the four variables. We used runoff as the first variable for the classification as it is the main concern for water resource management, and other three variables are 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 global scale except for Greenland, where models performance is questionable due to its particular conditions, and Antarctica, where the EU-WATCH product did not cover. The analysis for the world's largest 35 basins was performed considering the spatial average of each variable.

Among all the model output from EU-WATCH, we put particular attention 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 (Sect. 5).

4 Results

In this section, we describe the results of recurrence based on AC from the WaterGAP model as the representative case. The next section discusses the differences in results for the other metrics and the rest of the different models' results. Figure 3 shows the global distribution maps of the recurrence (i.e. AC in this case) in the four variables: precipitation, evaporation, storage and runoff. The map identifies the areas with very low recurrence (< 0.5) low recurrence ($0.5 \sim 0.75$) and high recurrence ($0.75 \sim 1.0$). 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 (0–23.5°), Subtropical (23.5–35°), Temperate (35–55°) and Subarctic and Arctic (55–90°).

The precipitation in the tropical region is basically characterized by the seasonality caused by the oscillation of the Intertropical Convergence Zone, and energy supply due to the effects of the earth's tilt fluctuation. Because of this seasonality, two bands between (5–23.5°) for both hemispheres show high recurrence in all variables, while they are lower in general at the equatorial band between 5° S and 5° N where there is no seasonality.

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 the four variables tend to have low recurrence. The Southeast Asia Monsoon area is an exception since its behavior is similar to the humid tropics area, 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 seasonality 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 with comparatively low recurrence in general.

Subarctic and arctic region shows low recurrence except for some areas in North America and Western Siberia. Evaporation exhibits the higher recurrence in this area. The extent area of high recurrence in storage and runoff is larger in this region mainly attributed to the amount of snow.

By taking the average of recurrence measures for each variables and following the classification tree illustrated in Fig. 2, the largest 35 river basins are classified. Figure 4 shows the result of the classification, which is described below according to each latitude region. Table 2 provides a summary description of each of the classes found with the respective basins that belong to it.

4.1 Tropical region (0.0–23.5°)

In the tropical region, there are mainly two patterns that can be observed in runoff. High recurrence in runoff takes place in the most humid basins exemplified in Fig. 6a by Amazon (QPES) and Fig. 6b by Orinoco (QPS). Basins with high recurrence in all variables are the result of all variables following the same pattern as precipitation as it can be seen in the Amazon time series in Fig. 7a. In Orinoco basin the variables of storage and runoff also follow the pattern of precipitation but evaporation is maintained constant as the basin is energy limited and potential evapotranspiration is constant resulting in low recurrence in evaporation.

On the other hand, 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 Figs. 6 and 7. These basins are drier than basins with recurrent runoff and are water limited in some periods in a year and have less runoff ratio than the basins with recurrent Q. PES basins are characterized by peaks in precipitation and potential evapotranspiration taking place at a different time of the year as seen on the Zambezi River's climatology in Fig. 6. As a result the storage fluctuates largely because it fills in the wet season and nearly dries in the dry season (Fig. 7c). This creates a strong seasonal pattern leading to high recurrence. PE class is characterized by the peaks of potential evapotranspiration and P peaking at the same time (Fig. 6d: Congo PE). Compared to Amazon, average precipitation is much lower but potential evapotranspiration is almost the same. The Congo basin can be energy limited ($P > \mathrm{PET}$) in the wet season, therefore regardless the amount in precipitation, evaporation will reach its potential creating more recurrent pattern 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 decreasing recurrence. Sao Francisco basin is an exception in this region consisting only of recurrent evaporation. This type of basin can be seen in the temperate region.

4.2 Subtropical region (23.5–35.0°)

In subtropical region, mainly two classes are observed. QPES river basins are located in Southeast Asian Monsoon, where similar behaviors are observed as river basins belonging to the QPES class in the tropical region. On the other hand we can observe the basins that are extremely dry, represented by Orange basin in Fig. 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. none of the variables are recurrent). The Indus river basin is an exception in this region belonging to the E class.

4.3 Temperate region (35.0–55.0°)

In the temperate region there are three particular classes observed: PE, ES and E. All of these classes have low recurrence in runoff and high recurrence in evaporation due to the seasonality.

A dominant class in this region is the ES class exemplified by the Mississippi Basin in Fig. 6. In this type of basin the precipitation pattern is not recurrent without a distinct dry season. Due to the limited energy during the winter season, precipitation is directly transferred to storage increase. During summer, the basins in this class are characterized by being water limited, and therefore most of the precipitated water is evaporated allowing for storage to decrease. As a result, the storage pattern shows higher recurrence. In these basins there is some influence of snow, however, the amount of snow is not as high as to create a recurrent runoff pattern.

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

Lastly, basins located in Eastern Asia belong to the PE class explained previously on the Tropical Region section. The reasons for these class to be taking place are the same for the temperate region that for the tropical region.

4.4 Subarctic and arctic region (55.0–90° (N/S))

In the subarctic region we found basins belonging to the QPES, QPE, QES, QE and E classes. Precipitation patterns vary widely depending on climatology. Basins with continental climatology exhibit less recurrence in precipitation than basins that receive some inflow of moisture from the ocean (Figs. 3 and 4). This creates the spatial patterns observed in Asia and North America, where a clear regionalization of basins in the QP- and QE- classes exist. All the basins in this region are water limited during summer (Fig. 6h–j), therefore most of the water available for storage changes and runoff generation is the water precipitated during winter. Recurrence in evaporation is highest in this region than any other region due to the high seasonality of energy. The climatologies of these basins (Fig. 6h–j) show that storage peaks during the winter months due to the accumulation of snow. Additionally, as can be seen from Fig. 8, the largest changes in storage take place in the snow component. Runoff is mostly driven by snowmelt, observed in the sudden peak in runoff during spring (Fig. 6h–j). Figures 9 and 10 show the snow water equivalent and seasonal precipitation amounts. From these two figures, we can observe that basins with higher snow amount have higher recurrence both in storage and runoff. 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.

5 Discussion

5.1 Characteristics of recurrence measured by AC

In this section we discuss general characteristics of recurrence measured by AC from monthly variables with the lags of 12 month multiples. Foremost, it is intrinsically sensitive to the seasonality; a higher seasonal variable tends to show a higher AC value. The reason is that the same magnitude of anomaly has smaller relative impact if a variable has high seasonality (e.g. for a variable with a range of 100, an anomaly of 10 represents a 10 % change while in a range of 50 it represents 20 %).

Despite seasonality enhancing recurrence in most of the cases, there can be exceptions where variables are not recurrent but they are seasonal. Figure 11 shows the monthly average precipitation in Ob and Yenisei. The two basins are located in the same latitudinal region sharing their border. The climatology of both basins is similar with comparable magnitudes at all months. However, the year to year variability and the fluctuation bands in both basins are different; Ob shows higher fluctuation than Yenisei. Therefore the precipitation in Ob has low recurrence (0.65) and Yenisei has high recurrence (0.88).

The recurrence of storage and runoff is dependent on the anomalies in precipitation relative to their volumes. The case of Amazon and Congo, aforementioned in Sect. 4.1, has difference in recurrence of storage and runoff. For precipitation, both variables have similar relative variations but the total precipitation in Congo is about 70 % than the precipitation in Amazon. Additionally, the runoff ratio is smaller in Congo (0.4) than in Amazon (0.45). The physical meaning of this aspect is that there is less water volume in Congo transferring from precipitation into storage fluctuation and runoff generation. Hence, the same anomalies in precipitation have larger impact in Congo than in Amazon.

In drier areas, where the evaporation volume takes of a larger percentage of precipitation or is higher than precipitation, the recurrence in storage is also influenced by the timing of precipitation and evaporation. This feature has also been discussed and used as an indicator for hydrological classification by (Coopersmith et al., 2012). When precipitation and evaporation peak together, there is a portion of the volume of precipitated water that is immediately taken by evaporation leaving less water volume for storage variation and runoff generation, as is the case of classes such as PE and E. When such peaks take place at different time of the year, storage can increase during the wet season, and then decrease much more during the dry season creating a higher range of variation, increasing the recurrence in storage (PES and ES). In these cases the final volume transferred to runoff is still not high enough and the anomalies from precipitation still represent higher relative anomalies to runoff. From the basins included in the ES class, Mississippi has the precipitation peak at the same time as potential evaporation; however, potential evaporation is higher than precipitation at this time, and winter precipitation is still high to create a large storage fluctuation. Extremely humid basins have larger storage volumes which allow for larger supply of water to runoff allowing for anomalies in precipitation not to be so significant to the runoff pattern resulting in recurrent runoff (QPES, QPS).

5.2 Recurrence measured by FFT and Colwell's Contingency compared to AC

The proposed indices to measure recurrence are lagged AC, FFT 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 (dry basins) have high Colwell Predictability as seen on Table 3. For example, in the arid basins where all the variables are low most of the time except for abrupt peaks, AC and FFT show low values, while Colwell's Constancy and Predictability are high. However, these basins are rather low in Colwell's Contingency. 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 contingency's results are highly consistent with the results of AC and FFT. Contingency is not only consistent with the other indices but it also suits better the intention of measuring recurrence as the interest is in the measure to which variables are at the same state at the same time slot (month) of different time cycle (year).

Figure 12 shows the correlation between AC and FFT and AC and Colwell's Contingency with the WaterGAP model with the basin's spatial average variables. All indices correlate well although there are particular cases that lie outside of a linear relationship. As mentioned in the methodology section the threshold selected for AC was 0.75. For FFT and Colwell's Contingency measures thresholds of 150 and 0.25 were selected to minimize the number of basins categorized as different classes. Table 4 shows the classification of basins from different metrics.

FFT 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 13 exemplifies the different periodogram with their respective partial time series and climatology. Figure 13a shows the example of evaporation in Changjiang for which a highly sinusoidal pattern indicates high AC and FFT. Figure 13b shows an example of low recurrence with low AC and FFT. However there are two examples where the FFT value indicates low recurrence while AC indicates high recurrence. First, Fig. 13c (Congo-evaporation) shows a bimodal pattern which has a high AC but the FFT, 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 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 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 in Fig. 13d. For both of these cases with deviations from a sinusoidal function AC represents better the concept of recurrence because if the same pattern repeats, independent of the shape of the pattern, AC at lags 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.

5.3 Model uncertainty

Model differences and uncertainties have been widely discussed in literature about model intercomparison (e.g. Haddeland et al., 2011). Main differences among the models are attributed to evaporation and snow modules, as well as their storage components. Here we briefly discuss how the model structural differences affect the results in the calculation of recurrence. Figure 14 shows the boxplots containing the ranges of recurrence for every variable in all basins by the eight different models.

Very low uncertainty on recurrence is found in most of the tropical humid basins on the QPES class. Larger uncertainty is observed in storage variables in these basins. For the case of Brahmaputra GWAVA and MPI-HM are outliers in the recurrence of storage computing 0.025 and 0.546 respectively, while other models range between 0.922–0.958. Haddeland et al. (2011) highlighted the overestimation of evaporation on this basin due to the use of Thornwaite evapotranspiration scheme. 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 as compared to other models. MATSIRO model has a deep groundwater tank which in general generates less seasonal variation in runoff (Haddeland et al., 2011). This of course has an effect on the recurrence calculation and in many basins recurrence changes from high on all models to low in MATSIRO.

Models in the temperate zone have wider uncertainty bands 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 affect mainly in basins that are around the threshold zone between 0 to 1 °C where precipitation is partitioned between snow or rain and melting processes start (Haddeland et al., 2011). Although the uncertainty is large, most models indicate the same class for most basins. In subarctic basins where the influence of snow is much more important the uncertainty band is small but the WaterGAP represent 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 hence 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 uncertainty due to the differences in partition between evaporation and runoff in each model. MATSIRO 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 a seasonal cycle in MATSIRO increasing recurrence.

5.4 Future application of the classification framework

By deriving the classification framework based on recurrence we were able to identify key hydrological processes that determine the temporal behavior of hydrological variables. The interaction of the variables of precipitation, evaporation, potential evaporation and storage and their effect on runoff was particular to each class. A number of recent studies project future climate change in precipitation, potential evapotranspiration, and their seasonal patterns. With the proposed classification framework we have gained an idea of the control that variables have in hydrology and therefore are now able to understand changes more mechanistically in these variables and its effects as opposed to just let a hydrologic model project with climate projections. One method that has tried to analyze hydrological change in a mechanistic way has been the analysis of the climate elasticity of runoff (Sankarasubramanian et al., 2001; Yang and Yang, 2011; Vano et al., 2012). All authors have identified a limitation in missing the incorporation of storage into the analysis assuming that in the long term storage is constant. We hypothesize that the sensitivity frameworks could be enhanced with our classification by already highlighting dominant processes in particular classes and incorporating a storage component.

The inclusion of storage and to explain its temporal variations is a novel part of this classification study. This 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 and Sivapalan, 2009). Our classification remarks how storage is controlled and how it controls runoff in different classes. We identified that for particular classes, the effects of precipitation and potential evapotranspiration transfer directly to runoff, transfer to storage and storage transfers to runoff or the effects are buffered by storage and no longer transferred to runoff. Our framework can be utilized as a bench state of basins and analyze the shifts in classes or changes in the temporal variations due to hydrological change, similar to Coopersmith et al. (2014). For this, EU-WATCH has readily available datasets for the 20th century and projections into the 21st century to analyze the change in temporal patterns under different conditions. We hope that this future research will add to previous research that has highlighted the role of storage in hydrological change.

6 Conclusions

This paper 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 variable repeats in the same range year after year. The recurrence was measured using the mean of autocorrelations (AC) with the multiples of 12 up to 60 month lags, the intensity of Fast Fourier Transforms (FFT) and Colwell's Contingency Index. These measures were calculated at global gridded scale (0.5°) and at the 35 largest basins of the world based on the model forcing or output of the EU-WATCH dataset.

The recurrence of individual variables are 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. In the tropical region, there are essentially two distinct groups. The first group appears in humid tropical areas, where the seasonality in precipitation dominantly creates the seasonality in both storage and runoff, hence the river basins in the areas are classified into (QPES) or (QPS) depending on the recurrence in evaporation. The second group appears in less humid or semi-arid tropical areas, where the higher evaporation relative to precipitation generates a lower runoff volume. Hence small anomalies in precipitation create higher relative anomalies in runoff, reducing the runoff recurrence. In these areas, the recurrence in storage is controlled whether the peaks in precipitation synchronize the peak in potential evaporation (PE) or not (PES).

In the subtropical region, many of the river basins belong to (L) class with all variables having low recurrence, particularly in extremely dry or desert belts. The exception is in Asian Monsoon area where all variables are recurrent (QPES) just like the humid tropical region described above.

In the temperate region, evaporation is always recurrent due to high seasonality, while precipitation shows low recurrence in this region. In these circumstances, if potential evapotranspiration is higher than precipitation (i.e. water limited) in summer, the storage becomes low in summer and may increase again due to precipitation in winter, resulting in relatively high recurrence in storage (ES). Whereas if potential evapotranspiration is lower than precipitation (i.e. energy limited) in summer, the anomalies in precipitation transfers directly to storage and runoff, decreasing their recurrence, therefore they are classified into (E). The only exception in this region is in Eastern Asia, where both precipitation and evaporation are recurrent, more comparable in volumes and synchronized in their timings. These features are similar to what were described in less humid tropical areas (PE).

In the subarctic region, evaporation is again highly recurrent due to extreme seasonality. Precipitation is recurrent in areas with oceanic currents influences, evident in some parts of North America and Asia. Recurrence in storage is found to be higher in the basins with larger amount of snow, whose melting process dominate the patterns of runoff. As a result, the runoff recurrence is found to be high in this region, while the storage recurrence varies in different areas. Therefore, the river basins are classified into QPES, QPE, QES or QE depending on their combinations. Finally, there are a few exceptions of basins classified as E in all regions, where evaporation is recurrent due to a particular seasonal pattern.

The above results were primarily obtained based on the analysis of AC metric with WaterGAP model output. However, the other two metrics, FFT and Colwell's Contingency, also showed highly consistent results. For a time series not following sinusoidal pattern (i.e. bimodal or sudden peaks), FFT becomes relatively low. Colwell's contingency depends on the amount of classes or intervals used for the analysis. In terms of the uncertainty due to the model selection, the metrics are also consistent among all the eight models, especially in humid river basins. There are particular models handling storage in a different manner which affects the amplitude of the seasonality or the runoff/evaporation ratios, resulting in different recurrence in some river basins.

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

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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 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 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, and 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 only classification framework, the analysis comparing different classes provide useful insights into the functions of large river basins in the world.

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Table 1. Overview of models included in this research and their characteristics. Adapted from Haddeland et al. (2011) and Gudmundsson et al. (2012a, b). 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).

Model Name	Precipitation input	Storage components	Provided PET	Reference
GWAVA	*P*	GM, SM, SWE	No	Meigh et al. (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 et al. (2003)
LPJmL	*P*	GM, SM, SS, SWE	Yes	Bondeau et al. (2007), Rost et al. (2008)
MATSIRO	*R*, *S*	SM, SWE	No	Takata et al. (2003), Koirala et al. (2014)
MPI-HM	*P*	SM, SWE	Yes	Hagemann and Dümenil (1997), Hagemann and Gates (2003)
WaterGAP	*P*	GM, SM, SS, SWE	Yes	Alcamo et al. (2003)

Table 2. Summary of class characteristics.

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 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	Precipitation 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	Precipitation, Storage and Runoff have a recurrent pattern but the constant the high water and low energy supplies create a constant 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 precipitation in winter does not allow a recurrent pattern in storage because of low snow volume, however runoff is recurrent
PES	Tocantins, Zambezi	Tropics (Southern South America and Africa), Temperate (East Eurasian Continent affected by Oceanic atmospheric flow)	Tropical humid basins with PET peaks at different time as P	Desynchronization of the Precipitation and PET cycles allows for filling of storage and also emptying during rainy and dry seasons respectively. Runoff is only generated for extreme precipitation due to lack of saturation in storage
PE	Amur, Congo, Huang He, Okavango, Plata		Basins with high evaporative index (0.7–0.8) with PET peaking at the same time as P	Runoff generation and storage change are highly limited by evaporation due to the synchronization of precipitation and PET storage changes
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	Storage increases during winter regardless of the precipitation pattern, however snow volume is not such as to pass the pattern onto runoff
E	Danube, Indus, Kolyma, Nelson, Sao Francisco, St. Lawrence		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 precipitation patterns transmit directly on to other variables, but evaporation is recurrent due to the seasonal availability of energy
L	Colorado, Darling, Grande, Orange	Subtropics (Desert Belt)	Arid basins	Irregular precipitation transmits to other variables as isolated events are the only water available for any hydrological process to take place

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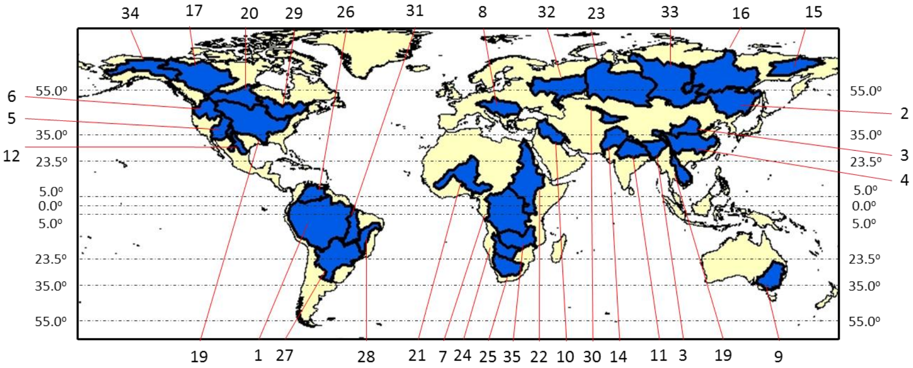
Table 3. Results of Colwell's Indices (Constancy – C, Contingency – M and Predictability – P) for all variables in arid basins. Constancy has high values due to variables being constantly low increasing the total predictability index.

Basin	Variable	C	M	P
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 4. Classification using different metrics, AC (AC), Colwell's Contingency (M) and Fast Fourier Transforms (FFT).

Basin	AC	M	FFT
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
Zambezi	PES	PES	PES



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. Location of the basins included in the analysis with an assigned identification number. The latitude reference lines identify the latitudes that divide each of the regions geographically separating the basins.

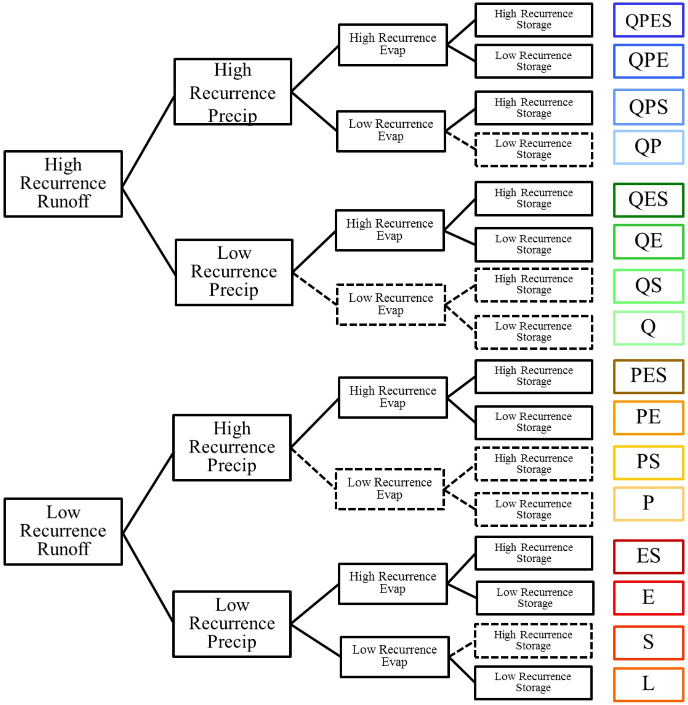


Figure 2. Hydrological classification tree. Color codes indicate the colors used in further maps to identify the classes to which basins belong. Dashed lines indicate paths into classes that were not found upon the studied basins. The existing classification were further subdivided into five main groups according to the main variables that have high levels of recurrence.

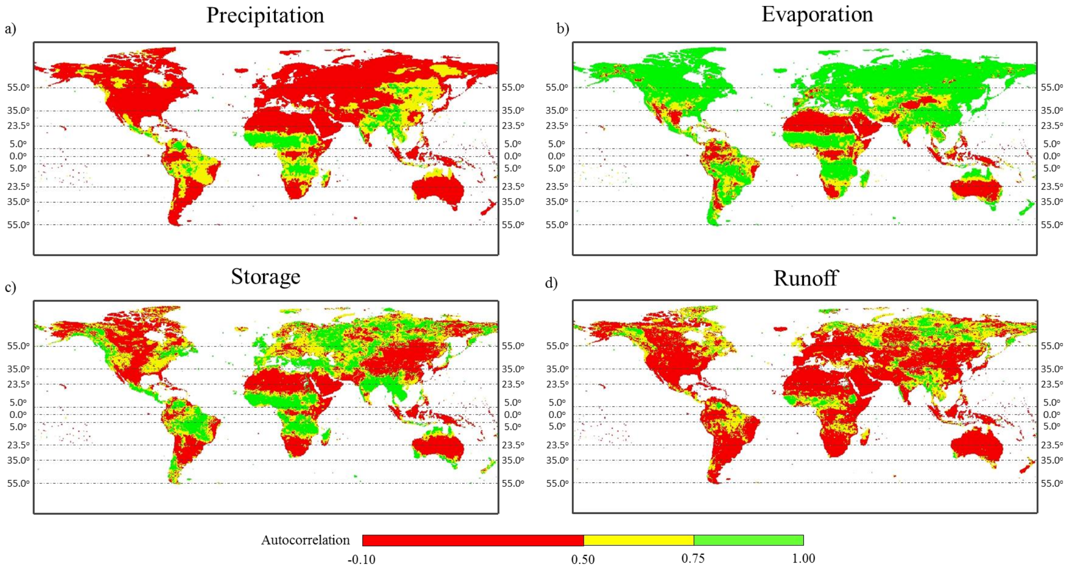


Figure 3. Recurrence in main hydrological variables at global scale: **(a)** precipitation, **(b)** evaporation, **(c)** storage and **(d)** runoff. The map identifies the areas with lowest recurrence (< 0.5), low recurrence (0.5–0.75) and high recurrence (0.75 <). Reference latitude lines identify the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

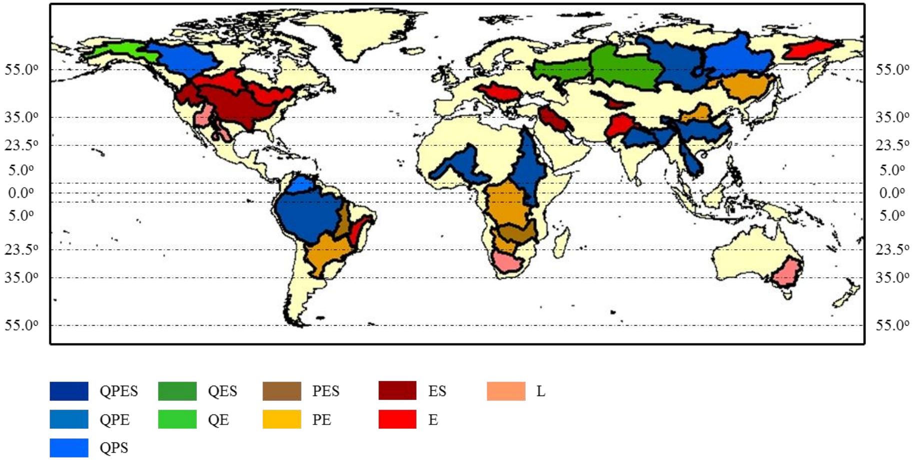


Figure 4. Basin location map with identification by class. A threshold for defining high recurrence or low recurrence was set at 0.75 average AC for multiples of 12 up to 60 months lag. Latitude regions were defined between the reference lines shown on the map for both hemispheres delimiting the Tropical Region between (0.0–23.5°), Subtropical Region between (23.5–35.0°), Temperate Region (35.0–55.0°), and Subarctic and Arctic Region (< 55). Particular classes were found to dominate in each of the different regions depending on the dominant hydrological processes.

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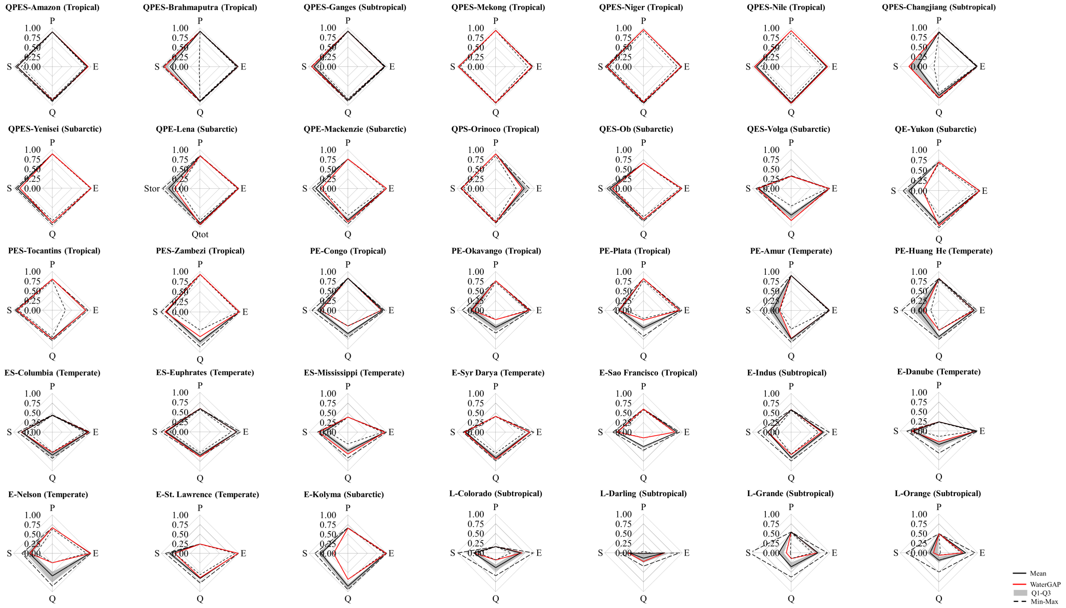

Figure 5. Radar charts depicting the results of recurrence for each variable in each individual basin. Results from the WaterGAP model are highlighted in red, the model mean is shown as a solid black line, the interquartile quantities are shaded in grey, and the max. and min. values are shown with a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

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Hydrological recurrence as a measure

R. Fernandez and T. Sayama

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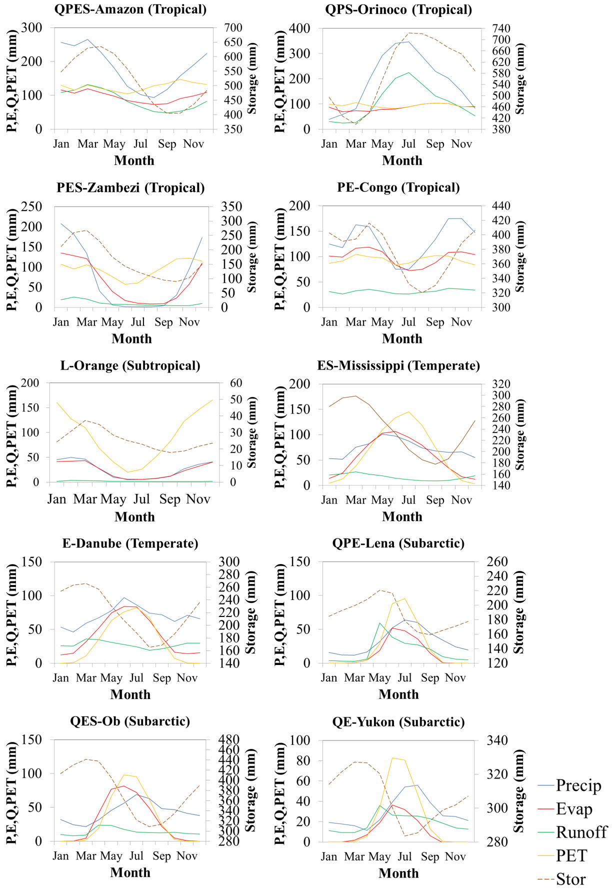

Figure 6. Variable climatologies for selected basins for each class and region. The charts present a particular basin for each of the 10 classes found sorted by region. Comparable axis of precipitation, evaporation, runoff and potential evaporation are shown on the left vertical axis and storage axis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

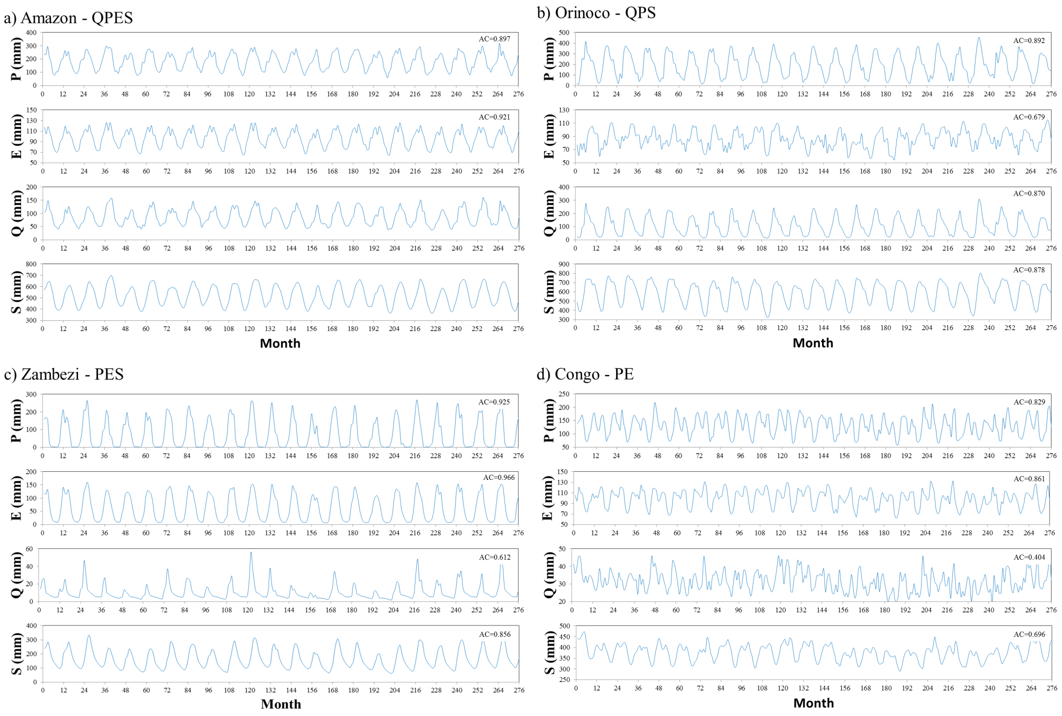

Figure 7. Monthly time series of selected basins in the tropics from each class: **(a)** Amazon – QPES, **(b)** Orinoco – QPS, **(c)** Zambezi – PES, **(d)** Congo – PE. The graphs exemplify time series with high or low recurrence depending on the classification. The averaged AC coefficient is provided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

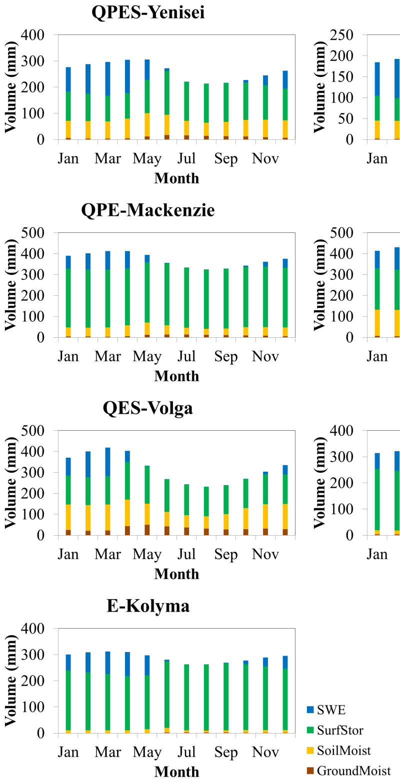

Figure 8. Climatology of storage and the various storage components for subarctic basins. Though SWE is not the largest volume for all basins the largest storage change takes place as snow melts in Spring and passes on to Soil Moisture or as direct runoff.

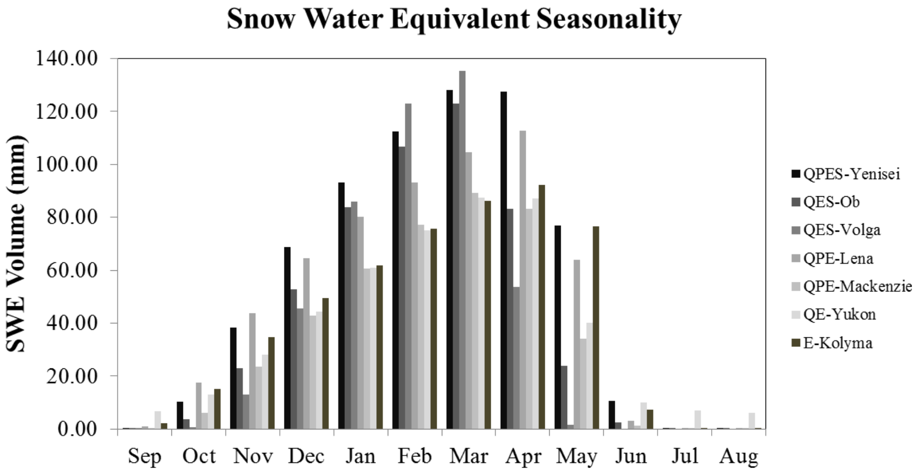

Figure 9. Snow water equivalent seasonality of sub-arctic basins. Storage change patterns in these catchments are mainly dominated by snow. Recurrence in storage and runoff is highly dependent on the amount of snow present in the basin. Basins which have higher snow water equivalent also have high recurrence in storage and runoff.

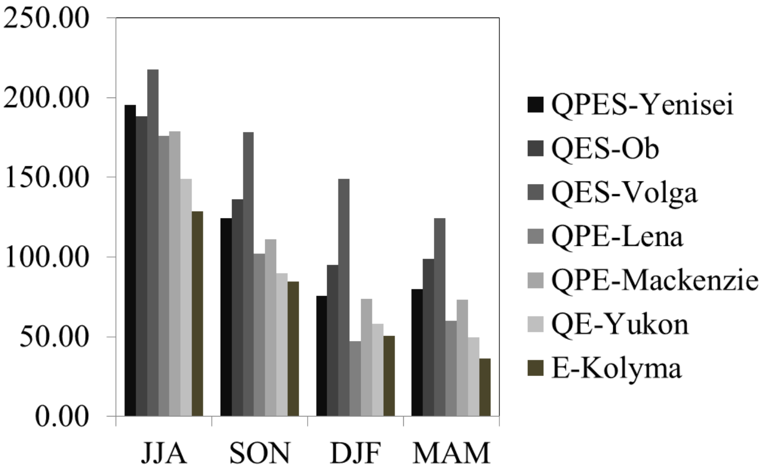

Figure 10. Seasonal precipitation climatology of sub-arctic basins. Basins with higher precipitation in SON, DJF and MAM are the basins with recurrent storage. Kolyma with the least precipitation throughout has lowest recurrence in runoff.

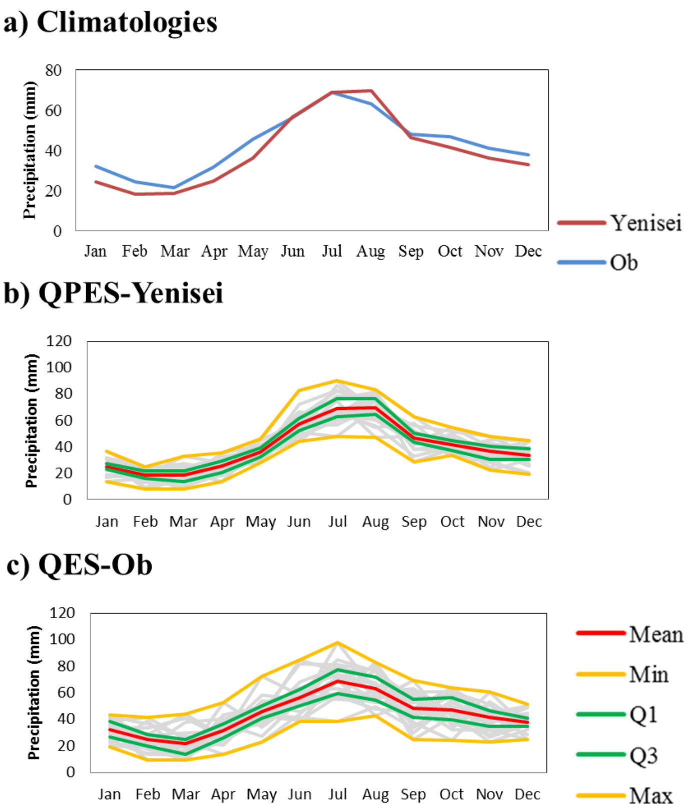

Figure 11. Seasonal storage change in basins of PES and PE class. Storage change is calculated by subtracting the month with minimum storage volume from the month with higher storage volume in the climatology.

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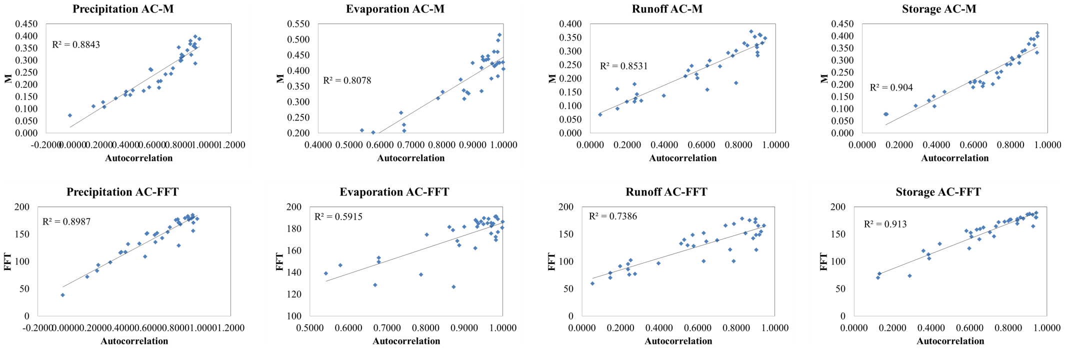

Figure 12. Comparison of AC with Colwell's Contingency (*M*), and FFT. In general, both indices correlate well, however it is difficult to set a threshold that divides the same basins in similar classes, mostly on variables that fall close to the selected threshold. Some outliers can also be identified from these scatter graphs.

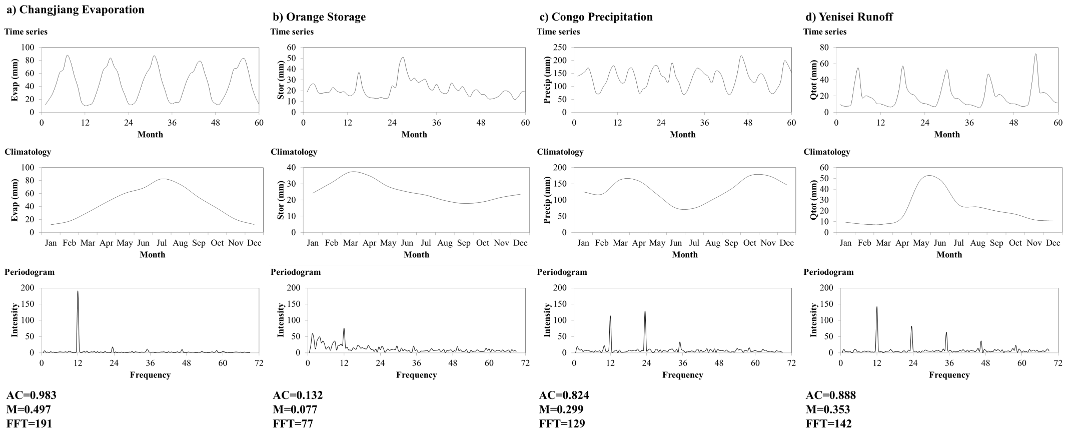

Figure 13. Examples of variables with different results in FFT. **(a)** Changjiang's evaporation has high AC, it has a simple rising and receding climatology and it results in high intensity in the FFT at frequency 12. **(b)** Storage in Orange is one of the variables that showed least recurrence as it does not have a well-defined pattern despite having a defined climatology. **(c)** Precipitation in Congo has a bimodal distribution. Despite having high AC the intensity of the FFT is distributed between the two peaks. **(d)** Runoff in Yenisei has a high peak in spring due to snowmelt and then it has a lump in summer when precipitation is higher The noise due to the lack of patterns results in reduced in intensity at the frequency of 12 and in higher intensity at other frequencies.

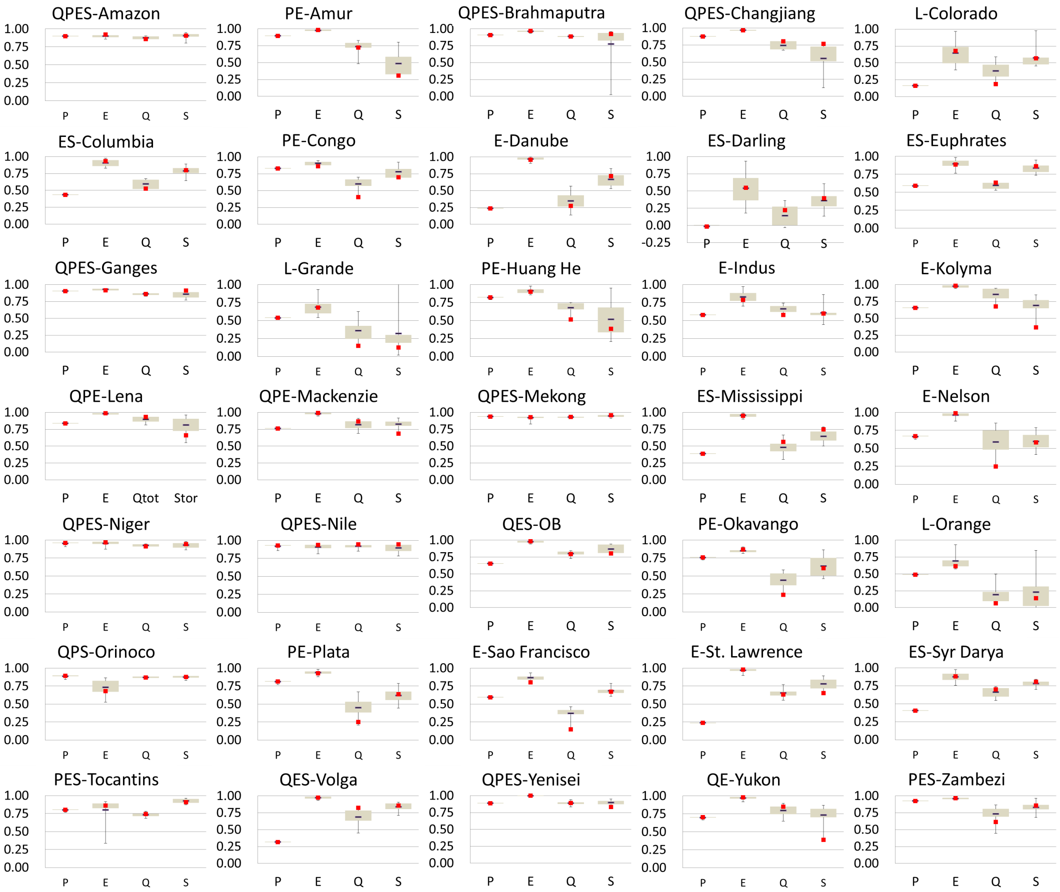

Figure 14. Model Uncertainty. Box plots show the recurrence measure for each variable in each basin displaying an interquartile uncertainty band, WaterGAP marked by the red mark, the mean highlighted by the black mark and the maximum and minimum values.