5 Prediction of annual runoff in ungauged basins

5.1 How much water do we have?

Human civilization depends upon a reliable water supply. One critical role of practical hydrology in delivering this supply is estimating the reliability of water resources available for meeting human and environmental needs. Two key elements of water resources planning are the long-term mean rate at which river runoff is generated, and its variability from year to year over time. For example, water supply reservoirs are designed to buffer out fluctuations in inflows and provide a reliable yield of water to sustain human needs. Successful reservoir design must therefore account for the mean and inter-annual variability of river inflows. Inter-annual variability also provides a way to quantify its sensitivity to variations in driving factors such as climate. Fundamental understanding of the nature and causes of variability of annual runoff is critical in assessing how the reliability of water supplies will change when the drivers of variability might change in the future, e.g., future climate change, land use and land cover changes. Such climate change, land use and land cover changes will require that water supplies are designed to operate under a different set of conditions than past climate (see Chapter 7). This chapter provides an overview of the processes and drivers of annual runoff variability in ungauged basins.

Mean annual runoff is the average of annual runoff values estimated over many years. Its inter-annual variability is usually quantified in terms of the standard deviation (or coefficient of variation) of annual runoff. It can also be expressed in terms of the growth curve (i.e., cumulative frequency distribution scaled by the long-term mean, see Chapter 9 for examples in the context of floods) of the annual runoff. Although commonly treated as constants, it is now recognized that both the mean and inter-annual variability of runoff may change over time as a result of long-term (natural) changes in climate, catchment characteristics, and anthropogenic factors. For example, Kautsky (1987) and Vertessy et al. (2001) describe inter-decadal to century-scale changes in runoff due to river discharges since 1950s.

5.2 Annual runoff: processes and similarity

Figure 5.1 presents examples of mean annual runoff and annual runoff variability, from two catchments of similar size located in the USA, but in two contrasting climates: the mountainous West Virginia and the dry Southern California. The pictures are representative of the landscape and vegetation for the two catchments. The catchment in West Virginia (Figure 5.1, top row) has much higher mean annual runoff (close to 1000 mm/yr) with moderate inter-annual variability (range of about ±300 mm). The catchment in California (Figure 5.1, bottom row) has instead a very low mean annual runoff (below 50 mm/yr) but high variability between years (close to zero and exceeding three times the mean). It is interesting to explore why there is much less runoff but with greater variability in the Californian river compared to that in West Virginia. Predicting annual runoff in ungauged basins is the starting point for predicting all other runoff signatures in this book. Therefore, insight into the complex processes must be provided to understand how variability and degree of similarity between catchments can be defined.
can be used to group similar catchments. Relationships that can be used to extrapolate from ungaged to gauged catchments in hydrologically similar (i.e., homogenous) regions are developed, and their performance in making predictions for ungaged basins is reviewed.

5.2.1 Processess

Figure 5.2 illustrates runoff variability for a catchment in New Zealand across a range of time scales. From less than hourly to inter-annual variation. Runoff variability at the annual scale (red line) is an aggregate measure that is damped compared to the high-frequency variation, but can be affected by some events by the presence of extreme-scale or seasonal fluctuations. Potentially, the inter-annual fluctuations in runoff could be disregarded as a component that reflects and potential evaporation, and a component that reflects the temperature and precipitation, especially in relation to potential evaporation (Morant et al., 2006), and is sensitive to higher-frequency variations in rainfall-runoff processes (Johangang and Swapavan, 2009). The term "event" is used throughout this book to describe high-intensity precipitation that is embedded in the weekly water budget, is also ultimately reflected in the type (e.g., physiology) and dynamic behaviour (e.g., photosynthesis) of the vegetation cover. The soil characteristics and the landscape slope, which can evolve on time scales from years to millennia, can be influenced by natural and human factors, such as for the Williams River, precipitation always exceeds potential evaporation at the annual scale, so that the ratio of runoff to rainfall is always greater than unity. The next sections describe the processes underlying annual runoff variability, including climate forcing, climate (biophysical) processes, catchment (physiographic) processes, and regional climate change.

Climate forcing

Annual water balance and annual runoff variability are governed, first order, by the relative availability of water (storm and inter-storm) scale up to the seasonal (wet and dry season) scale. Two distinct phases can be seen in a catchment's response to individual precipitation and individual runoff events, which are associated with the wetting phase, the first phase of runoff events, and another with the drying phase, when evaporation becomes a dominant process. Some processes, such as deep percolation of surface and subsurface drainage, operate continuously during both phases.

The catchment's response to the wetting phase depends upon precipitation characteristics (water inputs), catchment properties, and antecedent wetness, the occurrence of previous storms. The catchment's response during the drying phase depends on: (i) the water release characteristics of catchment storage, determined by topography, geology at time scales and by differences in topography, geology at long time scales and by differences in topography; (ii) the relationship between evaporation and precipitation events, which depends on the nature, extent, and intensity of precipitation; and (iii) the relationship between evaporation and precipitation at the catchment scale. The history of these interactions over seasonal and annual periods is embedded in the water budget, but is also ultimately reflected in the type (e.g., physiology) and dynamic behaviour (e.g., photosynthesis) of the vegetation cover. The soil characteristics and the landscape slope, which can evolve on time scales from years to millennia, can be influenced by natural and human factors, such as for the Williams River, precipitation always exceeds potential evaporation at the annual scale, so that the ratio of runoff to rainfall is always greater than unity. The next sections describe the processes underlying annual runoff variability, including climate forcing, climate (biophysical) processes, and regional climate change.

Differences in the availability of water and energy can explain much of the annual runoff variability observed in nature, as in the case of the catchments shown in Figure 5.1. The climate in West Virginia is humid, which means that on an annual time scale more water arrives in the catchment than energy can remove it through evaporation. Therefore, the magnitude of annual runoff in the West Virginia Williams River is always high. In contrast, Southern California has an arid climate. More energy is available to evaporate water than precipitation provides to the catchment. Hence, evaporation is high and mean annual runoff in the Santa Ynez Creek is low. More interestingly, the aridity of the climate also determines the high between-year runoff variability, because of the non-linearity of the rainfall-runoff relationship. This is due to threshold effects (e.g., the fact that, depending on the year, precipitation can be higher or lower than the potential evaporation) that mean that small differences in precipitation can translate into much higher differences in runoff, even at the annual scale. In the Santa Ynez Creek, there are many years with zero runoff. In a humid climate, such as for the Williams River, precipitation always exceeds potential evaporation at the annual scale, so that the ratio of runoff to rainfall is always greater than unity. The next sections describe the processes underlying annual runoff variability, including climate forcing, climate (biophysical) processes, and regional climate change.

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and annual potential evaporation (used as a surrogate for energy available, see Milly et al., 1994a, b and Potter et al., 2001) coincide with annual maxima in potential evaporation (\(E_p\)) coincide with annual maxima in potential evaporation (\(E_p\)) in many regions of the world exhibits strong seasonality. In these regions, the water balance equation (water year) is a complex system influenced by climatic and hydrological processes. The water balance equation can be expressed as follows:

\[ E_t = P + R + W_{\text{surf}} + W_{\text{storage}} + W_{\text{loss}} \]

where:
- \(E_t\) is the potential evapotranspiration
- \(P\) is the precipitation
- \(R\) is the runoff
- \(W_{\text{surf}}\) is the surface water storage change
- \(W_{\text{storage}}\) is the groundwater storage change
- \(W_{\text{loss}}\) is the water loss (evaporation, runoff, etc.)

The water balance equation is a fundamental tool in hydrology and water resources management, as it helps to understand the fate of water in a catchment and the factors that control its availability for various uses. The equation is often used to estimate missing data or to validate models that simulate the water balance at a catchment scale.

**Catchments (physical processes)**

If the Budyko curve is used as a representation of the Earth's water cycle, the water balance equation can be expressed as:

\[ E_p = P \]

where:
- \(E_p\) is the potential evapotranspiration
- \(P\) is the precipitation

This equation suggests that precipitation is a key driver of the water balance in a catchment, influencing both the availability of water for evapotranspiration and the storage of water in the catchment. The equation also highlights the importance of understanding the relationship between precipitation and potential evapotranspiration in accurately modeling the water balance in a catchment.

**Runoff Prediction in Ungauged Basins**

Runoff prediction in ungaged basins is a critical aspect of hydrological modeling, particularly in regions where gauging stations are lacking. Techniques such as the Annulus Model (AM) and the SCS Curve Number (CN) method are commonly used to estimate runoff in such areas. These models rely on catchment characteristics such as elevation, slope, and soil type to estimate runoff potential.

**Prediction of annual runoff in ungauged basins**

The prediction of annual runoff is crucial for water resource management and planning. It involves estimating the total runoff from a catchment under given climatic conditions, which is essential for designing infrastructure, planning water supply, and managing water resources efficiently.

**Figure 5.6**

- **Figure 5.6a**: Conceptual sketch of the effect of precipitation (\(P\)) and potential evaporation (\(E_p\)) on runoff in a catchment. The ratio of actual evaporation/precipitation to the ratio of actual evaporation/precipitation for climate divisions according to wetness. The ratio of actual evaporation/precipitation is shown as a ratio in phase or out of phase in the continental USA. From Wolock and McCabe (1999).

- **Figure 5.6b**: Example of catchment processes that can impact on annual runoff. The watershed is a complex system influenced by climatic and hydrological processes. The water balance equation can be expressed as follows:

\[ E_t = P + R + W_{\text{surf}} + W_{\text{storage}} + W_{\text{loss}} \]

where:
- \(E_t\) is the potential evapotranspiration
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- \(R\) is the runoff
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The water balance equation is a fundamental tool in hydrology and water resources management, as it helps to understand the fate of water in a catchment and the factors that control its availability for various uses. The equation is often used to estimate missing data or to validate models that simulate the water balance at a catchment scale.
Cathcart (biological) processes

Vegetation cover affects both the wetting and the drying phases of the catchment's response to precipitation. Vegetation affects water availability on time scales ranging from individual storm events (of the order of minutes to hours) to evolutionary change of the order of centuries. Vegetation links water availability to biogeochemical changes, to long time scales the physical and biophysical component of catchments co-evolve.

In the wetting phase, the dominant effect of vegetation cover is to reduce water availability for catchment evaporation. Evapotranspiration losses tend to be inversely proportional to density and directly proportional to density and inter-plant competition.

During the drying phase, vegetation imposes significant changes on the dynamics of evaporation. First through systems other than evapotranspiration (dominant where there is ample water vapor and transpiration (dominant in arid areas) that is not available to vegetation cover in arid areas). When canopy closure is extensive, the canopy controls the microclimate below it (Lautermilch and Bradford, 2006). Figure 5.7). Vegetation also affects the aerodynamic roughness of the land surface, leading to the suppression of evaporation. Water runoff and infiltration rates are lower with individual vegetation (trees and shrubs). The extent of water availability and the vegetation growing in a given area, the location of higher biomass and transpiration fluxes can also influence the feedback between vegetation and soil properties.

Vegetation also displays adaptive features on seasonal and annual time scales. For instance, many plants are deciduous or have snow-covered leaves during periods of water stress, creating a relationship between leaf area of water stress, creating a relationship between leaf area index and water availability, and reducing the transpiration surface area, and reducing the transpiration rate. These relationships may allow water balance patterns to be inferred from observations of extract of vegetation in geniculate Horizons, which can be down to water tables in generate Horizons, which run off down slope. Figure 5.7). In forest ecosystems, the soil moisture index of vegetation (NDVI) is used to infer the percentage of vegetation coverage. Ultimately, the soil moisture index of vegetation (NDVI) can be used to infer the percentage of vegetation coverage.

The presence of vegetation modifies the average residence time. For example, the presence of vegetation in forest ecosystems can be used to infer the percentage of vegetation coverage.

Vegetation cover is therefore both a response to the partitioning of the water balance and a driver of the annual water balance dynamics. Vegetation is also a significant driver of weathering, of soil biogeochemistry, and a determinant of soil hydraulic properties (Thompson et al., 2000). The role of vegetation in modifying its local water balance and the hydraulic environment can result in a feedback on the vegetation. For instance, modification of soil hydraulic properties by vegetation can result in the formation of spatial patterns in vegetation distribution, in which bands of vegetation are interspersed with regions of bare soil (Bosch et al., 2009; Thompson et al., 2011).

In northern hemisphere rugged landscapes, the difference in energy balance between north- and south-facing slopes regularly leads to drought-adapted vegetation communities on the north-facing slopes, and mesic vegetation on the south-facing slopes. These vegetation differences are also reflected in differences in soil depth, and carbon and nutrient content (lower on the south-facing slopes) (Burnett et al., 2008; Klemmedson and Weisheit, 1992; Frantze et al., 1969). These differences alter the storage capacity and habitat quality of the slopes, providing a positive feedback that exacerbates the differences between slopes with different aspects, and ultimately driving both vegetation balance and shade evolution (with vegetation, for instance, suppressing erosion and runoff on north-facing slopes, e.g., Cerdà, 1998; Simbuoluagbeto et al., 2008).

Effect of global change

Given that the primary control of annual runoff variability in many parts of the world is the availability of water and energy, changes in the magnitude or timing of precipitation and temperature (or potential evaporation) could contribute to major changes in annual runoff. A first-order indication of the extent to which this could be approximated via the Budyko curve. Changes in mean temperature and mean annual temperature can be expressed in changes in the aridity index, E/P. Depending on one's perspective, a shift in climate, one could move along the Budyko curve and determine the new value of E/P. For example, if the potential evaporation remains constant, a decrease in mean temperature will increase E/P, and annual runoff would be expected to decrease. A dramatic illustration of this effect arises in south-western Australia, in a study by Catterick and Weiler. Annual runoff records in Jarrangbarn (near Perth) over the past 100 years indicate that annual precipitation has decreased in the past 100 years, and a decrease in annual runoff. This change can manifest differently in different environments, depending on the relative slope of the Budyko curve. These changes in annual runoff and land cover change on runoff has been the subject of many paired catchment studies around the world, focusing on the impact of climate change on the relationship between runoff and land cover change.
is considerable variability in the timing and sometimes directionality of water balance responses to change (Andreadis et al., 2004; Brown et al., 2005).

5.2.2 Similarity measures

The process controls on annual runoff variability described above point naturally to indices or similarity measures that can be used to organise regions into groups with similar hydrological characteristics. Similarity measures can be described to define runoff patterns, climate and catchment morphology.

Runoff patterns: Based on runoff data, the similarity between catchments can be expressed in terms of mean annual runoff (flow volume rescaled by catchment area), or in terms of a runoff ratio (or coefficient): the ratio of mean annual runoff to mean annual precipitation. Inter-annual variability can be expressed in terms of the coefficient of variation (CV) of annual runoff, or in terms of a growth curve (cumulative distribution rescaled by the mean). Catchment responses to dynamic changes in climate or land use can be captured in terms of runoff elasticity, i.e., proportional change in runoff divided by proportional change in the climate or land use factor. For example, the precipitation elasticity could be defined as the proportional change in annual runoff over the proportional change in annual precipitation.

Climate similarity indices: Within a region, with homogeneous climate (e.g., similar aridity values, similar seasonality of precipitation and potential evaporation), different indices in annual runoff relate to catchment properties, e.g., storage and vegetation uptake. Similarity indices to describe these processes should reflect soil water holding capacity, soil texture (or saturated hydraulic conductivity), topographic slope and vegetation cover.

A dimensionless similarity framework for quantifying the relative role of multiple factors in annual water balance is obvious climate similarity measure with a proven predictive capacity. Figure 5.9a shows a global map of the aridity index. Locations with high aridity index usually have low runoff ratios, i.e., mean annual runoff is a small fraction of mean annual precipitation.

Within-year variability and in particular the relative seasonality of (or phase difference between) precipitation and potential evaporation also impact runoff variability. This seasonality can be computed with a seasonality index, $S = \frac{\bar{P}_a - \bar{E}_P}{\bar{P}_a}$, where $\bar{P}_a$ and $\bar{E}_P$ are the means of the precipitation and potential evaporation curves. Figure 5.9b presents the global distribution of the phase differences between precipitation and potential evaporation. A combination of the aridity index and the relative seasonality are needed to predict annual runoff in some regions. For example, in Mediterranean climates (e.g., south-western Australia, Southern California, southern Spain etc.) observed runoff amounts are inconsistent with predictions made from the annual aridity index: the prevailing out-of-phase seasonality (Figure 5.9b) elevates seasonal runoff production. Figure 5.9c shows the inter-annual variability of annual precipitation, expressed as the coefficient of variation; it is typically largest in arid locations (Figure 5.9a).

Catchment similarity indices: Within a region with heterogeneous climate (e.g., similar aridity values, similar seasonality of precipitation and potential evaporation), different indices in annual runoff relate to catchment properties, e.g., storage and vegetation uptake. Similarity indices to describe these processes should reflect soil water holding capacity, soil texture (or saturated hydraulic conductivity), topographic slope and vegetation cover.

An example of catchment similarity indices is the aridity index, $E/P$, which is a measure of aridity. The index is calculated as the ratio of mean annual precipitation to mean annual potential evaporation. A value of 1 indicates an arid climate, while a value of 0 indicates a humid climate.

The aridity index is a useful tool for regionalising catchments and comparing their hydrological characteristics. It can be used to identify areas with similar climate and hydrological conditions, which can be grouped together for the purposes of water resource management and planning.

5.2.3 Catchment grouping

Catches grouping in the case of PUB. The prediction of runoff in ungauged catchments is based on what is observed in, and what can be understood from, other similar catchments. Similarity metrics provide a way of measuring the similarity between catchments in terms of the patterns of runoff. The next section of this chapter discusses how to use this information from measurements in a set of catchments to make predictions in another. This transfer requires approaches to group similar catchments together, and then to use this information for prediction.
Canopy and soil variables: average interception storage.

In this subsection, statistical methods are used to develop catchment characteristics. Methodologies are developed for each group individually to provide a regional overview of the study area at the times of annual flood peaks. Examples of fixed groups are the first two studies in Figure 5.10. Targeted groups are chosen for each site individually with a prediction. The groups are typically used in regional frequency analyses (e.g., flow index method or region-of-impact approach, see e.g., Morz and Bizlich, 2003). These studies include the development of different groups for each catchment. One example is the third study area at the site 5.0 of the崂山区 region. The final target grouping methods may lead to classifications that are more continuous in space (regions) or non-continuous (groups). The study area at the left of Figure 5.10 are the non-contiguous regions, while the one in the middle is subdivided into two non-continuous regions. Methods that yield contiguous or non-contiguous groupings implicitly exploit spatial correlation to other similarity measures. This is advantageous in homogenous landscapes with smoothly varying catchment characteristics. A possible advantage of non-contiguous groups is their greater flexibility to include catchments that are scattered in space, but are hydrologically similar.

In order to make predictions in ungaged sites, the site of interest needs to be allocated to the homogeneous groups, adding further predictive uncertainty to the analysis. For contiguous regions this step is usually straightforward, i.e., ungaged catchments are allocated according to their geographic location. For non-contiguous groups, an allocation rule needs to be defined based on available catchment characteristics for the ungaged site. Statistical methods such as discriminant analysis or classification trees (Le and Bizlich, 2006a) or Akayev's curves (Nathan and McMahon, 1990) can be used to derive decision criteria on the basis of available catchment characteristics from the data set of gauged catchments. The criteria are then applied to allocate ungaged catchments to groups. A number of methods, called pooling methods, are used for subdividing sub-catchments into sub-regions or catchment groups. They differ in terms of how the groups are delineated (i.e., which subjective reasoning or algorithm is used) and what information is used (e.g., catchment characteristics, catchment and runoff characteristics, seasonality, etc.) Most of the methods can be used for both fixed and targeted grouping (Le and Bizlich, 2006a, b) for a discussion of the state-of-the-art of grouping methods for low flows).

One example of a pooling method that involves subjective reasoning is the regional pattern approach. This approach assumes that a single model for runoff prediction applies to the entire study area, but that regional heterogeneity that is not captured in the model results in localised deviations from the predictions, called residuals. These residuals are then mapped and, if patterns in sign and magnitude are recognised, they are used to delineate contiguous regions that are assumed to be homogeneous. In general,
5.3 Statistical methods of predicting annual runoff in ungauged basins

To predict runoff signatures in ungauged catchments, transfer mechanisms are needed to link information from other catchments to the catchment of interest. Regional statistical techniques have been a topic of intensive exploration in this area. These techniques treat the prediction of a target variable as the problem of estimating a random variable, while explaining the maximum amount of the spatial variance. Similar statistical assumptions and structures are used for many different predicted runoff signatures. In Chapters 5 to 10 these methods are reviewed, after the topics of:

- regression methods, where specific runoff signatures are transferred based on their relationship with catchment and climatic attributes via some analytical expression; linear methods, which assume that a known, quantitative runoff, catchment or climatic signature is constant within a defined homogeneous region, except for a small varying scaling index;
- statistical and predictive methods, which exploit spatial smoothness of the runoff signature. Here 'spatial' may refer to either geographic space or a parameter space defined by catchment attributes;
- quantification of short records, which exploit the relationship between moments of short runoff records and runoff in neighbouring catchments.

5.3.1 Regression methods

Mean annual runoff

Regression models are one of the simplest statistical methods used to transfer information. They express the relationships between dependent and independent variables that are prime drivers of runoff (see Section 5.3.2) estimated through a statistical method. One alternative to statistical methods is the use of regional regression method. The classification is presented in Figure 5.16, for example, grouped catchments are classified in terms of mean annual runoff, precipitation and temperature in the USA.

More complex multivariate analyses include additional independent variables, e.g., hydroclimatic, area, elevation and land cover. Hawley and McCuen (1982) discuss the advantages of multivariate regression analysis to estimate mean annual runoff. Water yield estimation from regression methods are objectively reproducible, their bias is minimised by the method, and uncertainty associated with them can be quantified under explicit assumptions. A less evident advantage is that regression methods can capture relationships that are evident in the data, but for which no theoretical explanation is available, for example due to the co-evolution of vegetation, landscape and hydrological response. In regression models, mean annual runoff is related typically to geomorphic and climate characteristics. Examples for the USA include Lull and Stepper (1966) and Johnson (1970) for New England, Thomas and Benson (1970) for regions in the western, central and southern United States, Majewski et al. (1972) for areas of South Dakota, Hawley and McCuen (1982) for the western USA, and Vogel et al. (1989) for the northern USA. Vogel et al. (1999) have developed regional multivariate models to estimate mean and variances of annual runoff across 18 regions in the USA. The work of Vogel et al. (1999) is discussed further in Section 5.5.1. Figure 5.12 presents one case study in north-western Italy (Vignone et al., 2007a). The mean annual runoff was obtained by a non-linear regression with the mean annual precipitation and the catchment average elevation. Elevation provides a surrogate for temperature (and therefore vegetation, landscape type, snow processes and their seasonal variation). Cross-validation results are shown, along with the 90% prediction intervals for the regression in Figure 5.12b.

Danz et al. (2010) used principal component analysis to relate 51 years of annual runoff data for 11 stream gauging stations in north-west China to areal precipitation and catchment characteristics. The regional regression model accounted for 87% of the variance in the runoff estimates. The eight variables included in the model are annual precipitation, annual surface water evaporation, sub-basin centroid coordinates, sub-basin centroid elevation, sub-basin area, sub-basin water area and sub-basin shape factor.

Inter-annual variability

Kalinin (1971) was the first to develop a relationship to estimate the coefficient of variation of annual runoff (CV). The CV was related to the catchment area through a two-parameter, decreasing, non-linear relationship. The decrease of the CV of annual runoff with area is to be expected, as a result of space-time averaging. McMahon et al. (1992) related the CV to the mean annual runoff with a power-law relationship, which
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Figure 5.12. Mean annual runoff estimated from regressions vs. observations. The dashed lines correspond to the 90% prediction interval. The map shows the location of 47 catchments in north-western Bavaria. Adapted from Vigneault et al. (2007).

Figure 5.13. Coefficient of variation of annual runoff versus mean annual runoff. Dashed line relates to Australia and Southern Africa (ASA), solid line relates to the rest of the world (RoW). From McMahon et al. (2007b). Note: for a given annual runoff, the CV in Australia and Southern Africa is significantly higher than the rest of the world.

5.3.2 Index methods

Index methods assume that the locally scaled signature of interest, or some functional form of it, is the same for all catchments in the group, which is called homogeneity. In the following, index methods for mean and variability of the annual runoff are discussed.

Mean annual runoff

Budyko-type models

Budyko-type models offer the potential to estimate mean annual actual evaporation from potential evaporation and precipitation without calibration. The index is computed as a ratio of the mean annual runoff to the potential evaporation. The latter is calculated as a function of the climatic homogeneity index and precipitation. The index is not a mass balance method, and it is not equally applicable to all regions. It is based on the assumption that the variability of the mean annual runoff is related to the variability of the precipitation.

Table 5.2. Functional (Budyko-type) relationships $F(p)$ plotted in Figure 5.14

<table>
<thead>
<tr>
<th>Model</th>
<th>Model details</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schreiber</td>
<td>$F(p) = \frac{1 - \exp(-p)}{\exp(-p)}$</td>
<td>Schreiber (1994)</td>
</tr>
<tr>
<td>Ol'denkamp</td>
<td>$F(p) = \frac{1}{1 + e^{-p}}$</td>
<td>Ol'denkamp (1991)</td>
</tr>
<tr>
<td>Generalised Taro-Pike</td>
<td>$F(p) = \frac{1}{1 + e^{-p}}$, $\alpha = 2$</td>
<td>Milly and Dunne (2002), Taro et al. (1994), Pike (1964), Budyko (1974)</td>
</tr>
<tr>
<td>Budyko</td>
<td>$F(p) = \frac{1}{1 - \exp(-p) + \sinh(p)}$, $\alpha = 0.5$</td>
<td>Budyko (1974)</td>
</tr>
<tr>
<td>Fu-Zhang</td>
<td>$F(p) = \frac{1}{1 + \exp(-p) + \sinh(p)}$, $\alpha = 0.5$</td>
<td>Fu (1981), Zhang et al. (2004)</td>
</tr>
<tr>
<td>Zhang two-parameter model</td>
<td>$F(p) = \frac{1 + \exp(-p)}{(1 + \exp(-p) + \sinh(p))^{\alpha}}$, $\alpha = 0.5$</td>
<td>Zhang et al. (2001)</td>
</tr>
<tr>
<td>Linear model</td>
<td>$F(p) = b \times p$</td>
<td>Potter and Zhang (2009)</td>
</tr>
</tbody>
</table>

The index is a function of $\alpha$ and $\beta$. The parameter $\alpha$ is usually smaller than 1. The relationship $F(p)$ is plotted in Figure 5.14 for a collection of Budyko-type methods listed in Table 5.2.

The index is sensitive to the input data and is not equally applicable to all regions. It is based on the assumption that the variability of the mean annual runoff is related to the variability of the precipitation.

Figure 5.14. $F(p)$ for a collection of Budyko-type methods listed in Table 5.2.

The index is calculated for a range of $\alpha$ and $\beta$. The relationship $F(p)$ is plotted in Figure 5.14 for a collection of Budyko-type methods listed in Table 5.2.

The index is sensitive to the input data and is not equally applicable to all regions. It is based on the assumption that the variability of the mean annual runoff is related to the variability of the precipitation.

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![Figure 5.16. Homogeneous regions and estimated growth curves for annual runoff in north-western Italy.](image)

(a) Result of cluster analysis in the space of catchment characteristics, \(F_{\text{avg}}\), average catchment elevation (in m a.s.l.), \(F_{\text{avg}}\), longitude of the center of mass of the basin (deg), where \(F\) is the homogeneity measure of Hisking and Walls (1997), (b) catchment areas in the geographic space; (c) Pearson type III growth curves associated to the four regions (P: non-exceedance probability); and (d) allocation rule for ungaged catchments in the space of catchment characteristics (\(x, y, z\): the parameters of the Pearson type III distribution). Adapted from Vigliocco (2007a).

is based on the hypothesis that while the mean annual runoff may vary between different sites within a statistically homogeneous distribution, the remainder of the probability distribution is identical. The regionalisation of the mean annual runoff is usually performed with one of the statistical methods addressed in Section 5.3.1, while pooling of data in homogeneous regions is used to estimate the regional growth curves (i.e., probability distributions defined by the mean). Vogel and Wilson (1996) present some applications related to the USA, while in Italy some previous works can be traced back to Ferrarese et al. (1988) and Cappa and Manconi (2002).

A case study of regional frequency analysis is provided by the study of Vigliocco (2007a), who performed an index flood regional frequency analysis in north-western Italy. The mean annual runoff was obtained through regression (see Figure 5.12), and the between-year variability of the annual runoff divided by the mean was considered fixed in homogeneous regions obtained through cluster analysis. Figure 5.16a shows the results of the cluster analysis (Ward algorithm and rectification) in the space of the similarity indices, in that case the mean catchment elevation and the latitude of the center of mass of the catchment. These two variables have the following hydrological interpretation:

- **mean elevation** is a surrogate for temperature and sea-level of snow processes; while latitude in the study area correlates to the climatic gradient from the driest south to the rainiest part of the region in the north.

Two catchment attributes are related to slope and shape of the growth curve (Garana et al., 2009). The number of clusters was selected using a homogeneity test (Hisking and Walls, 1997), and the homogeneous regions are shown graphically in Figure 5.16b. Figure 5.16c shows the estimated growth curves for four regions. The Pearson type III distribution was used to model the growth curves. Figure 5.16d shows how ungauged catchments in the region were allocated to the groups. The parameters of the Pearson type III distribution to be used as growth curves of the ungauged catchment were chosen by selecting the appropriate region based on its mean elevation and latitude. Regions 1 and 4 present the largest difference in the shape of the growth curves and are at the extremes in the attributes space. Region 1, corresponding to the Val di Non region in the north-west, is characterised by very high elevation and a cold-alpine climate. The between-year variability of annual runoff was less pronounced than in other parts of the study area, and in particular that in Region 4, located in the south and characterised by low elevation and a temperate climate. This higher runoff variability is attributed to higher mean annual evaporation and a more non-linear relationship between precipitation and runoff.
5.4.3 Cumulative and threshold methods of predicting annual runoff

In the cumulative method, the cumulative runoff is calculated by summing the runoff from each stream segment along the stream network. The threshold method involves setting a threshold value for the runoff, and the runoff in excess of this threshold is considered as the predicted annual runoff.

5.4.4 Derived distribution methods

A derived distribution method involves estimating the distribution of runoff from a known distribution of rainfall or other forcing variables. This method can be used to predict runoff under different climatic conditions or for different catchment sizes.

5.4.5 Artificial neural network methods

Artificial neural networks (ANNs) are used to model the complex relationships between input variables (e.g., precipitation, temperature) and output variables (e.g., runoff). ANNs can learn and generalize from historical data, making them suitable for predicting runoff in ungauged basins.

Figure 5.17 illustrates the use of ANNs to predict runoff in the Snake River basin. The network was trained using historical and future climate data. The predicted runoff is compared with observed data to assess the model's performance.

5.4.6 Observed hydrograph event

Observed hydrograph event refers to the observed water flow response to a particular rainfall event. This method involves analyzing the observed hydrograph and identifying the key features that characterize the event, such as peak flow, duration, and shape.

5.4.7 Precipitation event

Precipitation event refers to a specific period of rainfall, which is an important driver of runoff. The event precipitation is used to simulate the runoff using a hydrological model.

5.4.8 Analysis of historical climate data

Analysis of historical climate data involves examining the relationship between past precipitation and runoff to identify patterns and trends. This information is then used to predict runoff under future climate conditions.

5.4.9 Analysis of physical parameters

Analysis of physical parameters involves examining the physical characteristics of the catchment, such as topography, soil type, and vegetation. This information is used to predict runoff based on the expected changes in these parameters under future climate conditions.

5.4.10 Statistical methods

Statistical methods involve the use of statistical models to predict runoff. These models are based on empirical relationships between input and output variables, such as precipitation and runoff.

5.4.11 Model comparison

Model comparison involves comparing the performance of different models to identify the most accurate one for predicting runoff in a specific catchment. This is typically done by comparing the predicted runoff with observed data and using statistical metrics to quantify the model's accuracy.

5.4.12 Summary

In summary, predicting annual runoff in ungauged basins is a complex task that requires a combination of different methods. The choice of method depends on the available data, the spatial scale of the catchment, and the desired level of accuracy. The goal is to develop a model that can accurately predict runoff under future climate conditions, which will help in water resource management and planning.
equations over the distribution of inputs, to obtain the probability distribution of the model output. This technique is known as the derived distribution approach. There are many examples of applications of this approach in hydrology (e.g., Egleslie, 1972; Habson and Wood, 1982; Rawlins and Senarath, 2000; Swagol and Santiago, 2005). To estimate annual (or shorter-term) runoff, Budovsky-type models need modification to account for the catchment-water storage (Zhang et al., 2000a; Tokinab et al., 2011). Models that incorporate monthly or seasonal rainfall on lo- cal spatial variability of soil water holding capacity or seasonal variation in climate. He tested this method with- out mode calibration, for data from catchments located east of the Rocky Mountains in the USA. He concluded that the seasonal fluctuation of the forcings was always relevant, especially in grid catchments, while the effect of seasonal variation in climate and soil water holding capacity on annual runoff was negligibly small. By extending Mill's approach to include variable phase shifts in the representation of seasonal climate, Porter et al. (2005) modified esti- mation of the water balance model. Australian catchments' results are presented in Figure 5.20. Porter et al. (2005) established the probability distribution function of the annual runoff (Vogel and Wilson, 1996; McMahon et al., 2007a), and using this annual series data of the model that will allow more sophisticated analysis such as stochastic data analysis to be carried out (Matalas, 1967; Stedinger and Taylor, 1982). It is Hipel and McLeod, 1994; Thyer et al., 2002).

The difficulty in applying continuous model is twofold: (i) identifying an appropriate model structure and (ii) obtaining the necessary parameter set(s) that allow the model to produce plausible runoff values. Parameter regionalisation to ungauged catchments is often con- founded by poor parameter identification at gauged catch- ments. There are numerous sources of parameter uncertainty, including errors in input data, errors in model structure and errors of the calibration data. Even the choice of the objective function and optimisation techniques for calibration contribute to uncertainty (see Pea and Biltzich, 2007), and references therein). These issues are discussed in more detail within the PUBL framework (Chapter 10 and are not addressed here. There are few practical methods and only limited guidance for objectively assessing model structure for ungauged catchments (e.g., when using lumped conceptual models, more input catchments generally require more complex models). Once a model struc- ture is chosen, there are many methods for parameter estimation (see Section 10.4). Thus, the benefits of making high resolution temporal predictions trade off to some extent against the challenges imposed by mangnaing uncer- tainty in these predictions.

5.3.4 Proxy data on annual runoff processes

Tree ring chronology and paleoclimatology

Proxy data allow analysts to extend time series of annual runoff to periods prior to runoff observations. A statistical relationship, usually regression, is established between observed runoff and one or more proxy data series, which is then used to synthesise a time series of annual runoff driven by the long proxy records. An abundance of litera- ture exists where tree ring chronology or other paleocli- mate proxy records are used to develop satisfactory relationships with observed annual runoff data. The NOAA Satellite and Information Service (NOAA Paleocli- matology, 2011) lists runoff reconstructions for several US states, the Selenge River in Mongolia, and the Burdekin River and other Queensland rivers in Australia. Examples of recent runoff reconstructions outside the USA include the Canadian prairie rivers (Cave and Macdonald, 2003), the Churches River in northern Saskatchewan, Canada (1840–2002) (Beriault and Sauchyn, 2006), four rivers in coastal Queensland, Australia (Lough, 2007), the Murray River in Australia (1783–1988) (Gallant and Greggs, 2011), the Yellow River in western China (Guo et al., 2005).
The aim of the comparative assessment of annual runoff predictions in ungauged basins is to learn from the similarities and differences between catchments in different places, and to inspire the developers in performance in terms of the underlying climate-landscape control. Understanding these controls sheds light on the nature of catchments as complex systems and provides guidance on what methods to choose in a particular environment. The assessment is performed at two levels (see Section 2.4.3).

The Level 1 assessment is a meta-analysis of studies reported in the literature. The Level 2 assessment involves a more focused and detailed analysis of selected studies of Level 1 in terms of how the performance depends on climate and catchment characteristics as well as on the method chosen. In Level 1 and Level 2 assessments, the performance was evaluated by leave-one-out cross-validation (for just overall of the cross-validation results were not available). In the leave-one-out cross-validation, each catchment was related to ungauged and the runoff predictions were then compared to the observed runoff. The performance was evaluated by the comparative water supply estimates of the total uncertainty of runoff predictions in these ungaged basins.

5.5.1 Level 1 assessment

Table A5.1 lists the 34 studies evaluating mean annual runoff and Table A5.2 lists the 9 studies evaluating the inter-annual runoff variability used in the Level 1 assessment.
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Figure 5.22 and Tables A5.1 and A5.2 indicate that overall a good global coverage was achieved for annual runoff, the assessment in humid and cold climates dominates, while the inter-annual variability is mostly assessed globally over several climate zones.

The analysts from the literature were stratified using the climate classes based on the updated Köppen-Geiger climate classification of Peel et al. (2007). The following classification criteria were applied. All locations with mean annual precipitation lower than a threshold value are classified as belonging to the B climate in Peel et al. (2007) and as "arid" in this assessment. If 70% of the mean annual precipitation occurs in winter, the threshold (in mm) is 20 times the mean annual temperature + 24. Otherwise, the threshold is 20 times the mean annual temperature + 14. For areas where mean annual precipitation exceeds the threshold, other climate types are possible. In this assessment, the locations where the temperature of the coldest month is not lower than 18 °C are called "tropical" (A climate in Peel et al., 2007). The locations where the temperature of the hottest month is above 10 °C and the temperature of the coldest month is between 0 and 18 °C are defined as "humid" (C climate in Peel et al., 2007).

In this assessment, the locations with a Mediterranean climate (A sub and C sub) have been considered "arid", even though they would belong to the C climate in Peel et al. (2007). Finally, locations where the temperature of the coldest month does not exceed 0 °C are defined as "cold" (D and E climates in Peel et al., 2007).

How good are the predictions in different climates?

Figure 5.23 shows that the highest performances are obtained for the cold and humid catchments, while they tend to be lower in arid regions. This indicates that the prediction of annual runoff in regions with a surplus of water over energy is easier than in drier climates. The main reason behind this is that in and regions a higher feedbacks with physiographical characteristics (i.e., evaporation, geology and vegetation) complicate the estimation of annual runoff.

Which method performs best?

Figure 5.24 compares the performance of different methods for estimating annual runoff and inter-annual runoff variability. The regionalisation methods used here are regression, index methods, spatial proximity, and process-based methods for the performance of spatial predictions and methods using proxy data (i.e., tree rings) for the temporal accuracy of runoff estimation. The analysis includes ten results for annual runoff and ten results for inter-annual runoff for all of the methods used different regression approaches to estimate annual runoff characteristics.

The index method includes eight results for annual runoff and nine results for inter-annual runoff variability that applied different Budko-type models. The spatial proximity group consists of ten results for annual runoff.

These are all interpolation methods including geostatistical approaches. Process-based models are only rarely applied and are represented here by four results that used different rainfall-runoff models. Finally, eight results that estimate annual runoff based on proxy data are available. For annual runoff, spatial proximity methods show the best performance with median r² values close to 0.89. The four results are mainly from north-eastern USA and France where a considerable number of stream gauges exist. The performance of regression methods tends to be slightly lower. The studies come from a mix of continents. Two studies in Europe compared spatial proximity with regression and found significantly better performance of spatial proximity. In regions where annual runoff varies rather smoothly in space and where a reasonable number of stream gauges exist, it is not surprising that spatial proximity methods would perform well. It should also be noted that some of the results for the regression methods are based on volumetric runoff values (crosses in Figure 5.24) so, if only specific runoff is considered, the median performance is actually lower.

Index methods (such as Budko) also perform quite well, as far as well as or better than regression, considering that some of the regression results are for volumetric runoff. The performance of process-based methods (mainly runoff models) tends to be lower, with a median r² of around 0.7. Clearly, the performance strongly depends on the way the models are calibrated to existing runoff data. For completeness, methods that use tree ring (proxy) data were included but, unsurprisingly, suggest that the main focus of tree ring chronology is to reconstruct past runoff variability rather than to predict runoff in the present climate.

For the prediction of inter-annual runoff variability the regression and index methods perform similarly, with a median r² of 0.65 and 0.57 respectively. The results of the regression method have a much larger scatter. In general, the performance is somewhat lower than the performance obtained for mean annual runoff since, clearly, inter-annual variability is harder to predict.

How does data availability impact performance?

Figure 5.25 shows the predictive performance as a function of the number of catchments analysed in each study. Most of the studies used relatively large data sets, although this probably reflects the fact that most studies evaluate the accuracy of predictions in space. An exception is the prediction of temporal variability by proxy methods (i.e., tree rings), which is usually tested only on single catchments.

The results indicate that the performance does not seem to depend on the size of the data set. Apparently, only data from a small number of gauged catchments are needed in order to predict mean annual runoff within the study area in ungaged basins. There may be two effects related to scale. The first is that the total heterogeneity tends to increase as the size of a region increases, which would be expected to lower the performance if the same method is used in the entire region. The second is that, with increasing sample size, the methods may be adjusted more reliably to the existing runoff data. These two effects may counterbalance each other as the size of the data set increases. The prediction of inter-annual runoff variability, on the other hand, is more specific and improves with the availability of larger data sets.

More detailed insight into the dependency of performance on both method and number of catchments per study is shown in Figure 5.26. Index-based methods have been evaluated mostly for data sets with more than 200 catchments, while spatial proximity and regression methods...
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861 catchments located in 82 countries around the world. No data for the inter-annual runoff variability were available, so the Level 2 assessment presents only results for mean annual runoff. In order to identify differences in global and local scale analysis an additional assessment for 220 catchments in Austria was also performed (Viglione et al., 2013b). Based on the data availability and global coverage, three approaches were applied: two statistical approaches, global and regional regression, and a Budýko method. The normalised error (ANE) and the absolute normalised error (ANE) were used as performance indices (Table 2.2). The NE highlights biases in the methods, while the ANE is a measure of the overall performance. For comparison with the other runoff signatures in Chapter 12, the NE of annual runoff were calculated for all methods of both the global and the Austrian data. The 0.5% and 75% quantities of these NE are 0.52 and 0.81, respectively.

Performance measures are presented in the following figures as a function of the aridity index, mean annual temperature, mean elevation and catchment area. Note that the ANE is an error measure, so it has been plotted downwards on the vertical axis to make it comparable with the performance measures, i.e., higher up in the plot is better.

To what extent does runoff prediction performance depend on climate and catchment characteristics? Before analysing the NE and ANE of the three chosen approaches, a regression analysis of mean annual runoff with area, mean annual precipitation and mean annual temperature ($T_a$) was performed in order to understand which predictors are important for mean annual runoff under different climatic conditions. The $r^2$-value, calculated based on specific runoff, did not exceed 0.5 for any of the regressions. This indicates that the size of catchments and global climate variability control only part of mean annual runoff patterns. While all three predictors were significant for estimating mean annual runoff in humid, cold and arid conditions, the analysis showed that for tropical climates $T_a$ does not play any role.

The ANE error measure of mean annual runoff with respect to the four climate and catchment characteristics is presented in Figure 5.27. The results clearly indicate that the performance of all models decreases with increasing aridity (top panel). For global regression and regional regression the ANE is more suited for humid catchments and larger for arid catchments. For the Budýko approach, more errors in the arid catchments are smaller than in the other parts. Apparently the structure of the Budýko is more suited to predicting mean annual runoff across the continent for each catchment. This data set combines data from across the globe which may lead to underestimate mean annual runoff. It should be noted that the Budýko relationship was not calibrated but the regression coefficients were. The dependence of ANE on air temperature shows a similar, but less pronounced pattern. This means the difficult climates to predict are the arid catchments and not necessarily the catchments with a warm climate.

A clear relationship does not exist between ANE and catchment area. For regression models, the variability of ANE performance between catchments of the same size is larger than for the Budýko model. This variability is the largest for catchments larger than 1000 km$^2$. The Budýko model seems to be a robust method. Even though there is a tendency for underestimating runoff, the results are more consistent for a given catchment size.

Which method performs best? Figure 5.29 summarises the performance for different regionalisation approaches, stratified by the aridity index. The top, middle and bottom panels show the performance for all catchments, and catchments with an aridity index below and above 1, respectively. Overall the Budýko model performs better than the two regression approaches. Regional regressions perform better than global regression. While the performance in humid catchments is quite similar for all three approaches, in arid regions the performance of the Budýko approach is much better than that of regressions. The built-in principle of water versus energy competition included in the Budýko model appears to provide an inherent advantage for mean annual runoff prediction compared to purely statistical approaches, particularly in arid regions. It should also be noted that in arid regions the regional regressions perform significantly better than global regressions, while this is not the case in humid regions.

Global scale results vs. local scale results

The results of the Level 2 assessments compared the performance of statistical and index methods on a global scale. The performance of methods for mean annual runoff prediction in a particular region depends on the hydrological variability, as well as data availability. As an example, Figure 5.30 compares different approaches for mean annual runoff prediction in 220 catchments in Austria (Viglione et al., 2013b), which are generally in humid with the aridity index ranging from 0.2 to 1.4. The following methods were used: the global regression model fitted to the global data set of Peel et al. (2010) using catchment area, mean annual precipitation and air temperature as catchment characteristics; the Budýko approach; a regional regression model fitted to the Austrian data (using the same catchment characteristics as
for the global regression: catchment area, mean annual precipitation and air temperature; a process-based (conceptual soil moisture accounting model at the daily time scale); and a geostatistical method (top-kriging). Overall the performance is much better than that of the global predictions as one would expect given the higher data availability. The global regression model gives ANE of around 0.3 as opposed to 0.4 for all humid catchments of the Level 2 assessment (Figure 5.29) indicating that the Australian data set is in a range where the regression model works well. The Budyko model and the regional regressions perform better than the global regressions. Note, again, that Budyko was not calibrated to the Australian data, while the regional regressions were. The Budyko approach and geostatistics perform best in predicting annual mean runoff in ungauged basins. This indicates that the use of regional data can improve the predictions significantly beyond global methods. The results also point towards the strength of the Budyko model, which is very good even though it was not calibrated. The process-based approach and geostatistics perform best in predicting annual mean runoff in ungauged basins. This indicates that the use of regional data can improve the predictions significantly beyond global methods. The results also point towards the strength of the Budyko model, which is very good even though it was not calibrated.

Main findings of Level 2 assessment:
- The performance of all methods of predicting mean annual runoff in ungauged basins decreases with increasing aridity.
- There is a tendency for the performance of the regression methods to decrease with air temperature but no apparent dependence on catchment size.
Figure 5.30. Absolute normalized error (ANE) of predicting mean annual runoff in ungauged basins for different regionalisation methods, stratified by aridity: (Top) All catchments; (centre) humid catchments; (bottom) arid catchments. Lines connect median efficiencies for the same study; boxes are 40th–60th quantiles, whiskers are 20th–80th quantiles.

5.6 Summary of key points

- The Budyko approach tends to underestimate mean annual runoff. The regression models tend to overestimate runoff in arid catchments.
- In humid catchments, the Budyko approach and regression methods perform similarly.
- In arid catchments, the Budyko approach performs much better than the regression methods. Regional regressions perform better than global regression.
- In a regional case study, the performance of predicting mean annual runoff in ungauged basins for different methods increases in the following order: global regression, Budyko model, regional regression, process-based method and geostatistical approach.

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- Process-based methods, especially those that belong to the derived distribution category, can assist in interpreting the process basis of the index-based relationships (e.g., Budyko), help understand their applicability to different situations, and can explain the reasons for the scatter (and hence uncertainty) around the mean Budyko curve.
- Comparative assessment of all methods used for prediction of annual runoff in ungauged basins indicated that predictive performance decreases with increasing aridity (shown in both Level 1 and 2 assessments). Budyko-type index methods perform better in arid regions (Level 2 assessment) compared to regression approaches, as they are built around the principle of water versus energy competition. Spatial proximity methods (e.g., geostatistics) outperform other techniques (Level 1 and 2 assessments). They require stream gauges in the region of interest.
- Annual runoff variability represents the foundation (i.e., low frequency variation) on which all other runoff variability is built. Understanding annual runoff variability is the key to understanding the remainder of the variability found in the runoff hydrograph. Annual runoff variability is also the signature that best reflects the co-evolution of climate, soils, vegetation and topography. Therefore, there is much to be gained from understanding the nature of annual runoff variability and how it connects to vegetation, drainage density and other patterns, which are all a result of the same co-evolutionary processes. Comparative hydrology represents a clear way forward for the joint investigation of these co-evolutionary patterns across different parts of the world.
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