Catchment characterization: current descriptors, knowledge gaps and future opportunities

Larisa Tarasova[1,2], Sebastian Gnann[3], Soohyun Yang[4,5,6], Andreas Hartmann[7], and Thorsten Wagener[3]

[1]Department Catchment Hydrology, Helmholtz Centre for Environmental Research – UFZ, Halle (Saale), Germany
[2] Department of Earth and Environmental Engineering, Columbia University in the City of New York, New York, USA
[3] Institute of Environmental Science and Geography, University of Potsdam, Potsdam, Germany
[4] Department Aquatic Ecosystem Analysis and Management, Helmholtz Centre for Environmental Research – UFZ, Magdeburg, Germany
[5] Center for Advanced Systems Understanding (CASUS), Görlitz, Germany
[6]Department of Civil and Environmental Engineering, Seoul National University, Seoul, South Korea
[7]Institute of Groundwater Management, Technical University Dresden, Dresden, Germany

Corresponding author: Larisa Tarasova (larisa.tarasova@ufz.de)

Contact information: Larisa Tarasova (larisa.tarasova@ufz.de), Sebastian Gnann (gnann1@uni-potsdam.de) , Soohyun Yang (soohyunyang@snu.ac.kr), Andreas Hartmann (andreas.hartmann@tu-dresden.de), Thorsten Wagener (wagener1@uni-potsdam.de)

Twitter (X) handles: @lytarasova, @UniPotsdamWater, @sub_heterogenty, @thorsten1971

This is a non-reviewed preprint submitted to EarthArXiv.

Manuscript is submitted for consideration to Earth-Science Reviews.

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[3] Institute of Environmental Science and Geography, University of Potsdam, Potsdam, Germany
[4] Department Aquatic Ecosystem Analysis and Management, Helmholtz Centre for Environmental Research – UFZ, Magdeburg, Germany
[5] Center for Advanced Systems Understanding (CASUS), Görlitz, Germany
[6]Department of Civil and Environmental Engineering, Seoul National University, Seoul, South Korea
[7]Institute of Groundwater Management, Technical University Dresden, Dresden, Germany

Key words: systematic review; catchment descriptors, catchment attributes; catchment characteristics; spatial aggregation; subsurface structure; catchment functioning

Abstract

An ability to describe hydrologically relevant differences between places is at the core of our science. A common way to characterize hydrological catchments is to use descriptors that summarize important physical aspects of the system, often by aggregating heterogeneous geospatial data into a single number. Such descriptors aim to capture various facets of catchment functioning and structure, identify similarity or dissimilarity, and transfer information among them. However, so far there is no agreement on how catchment descriptors should be selected, aggregated and evaluated. Even worse, little is known about the existence of potential biases in the current practices to characterize catchments. In this systematic review, we analyze 742 research articles published between 1967 and 2021 to provide a categorized overview of current and historical practices of catchment characterization (i.e., data sources, aggregation and evaluation methods) in hydrological science and related disciplines. We uncover the existence of substantial biases in catchment characterization: (1) only 16% of the analyzed studies are in dry environments, even though such environments cover 42% of global land surface; (2) only 30% of studies use subsurface features for catchment characterization; (3) only 4% and 9% of descriptors are aggregated in spatially- and vertically-differentiated way respectively, while the absolute majority of descriptors are simple averages and do not account for hydrologically-relevant variabilities of features within catchments; (4) 25% of analyzed studies do not evaluate the usefulness and none of the analyzed studies quantify the uncertainties of catchment descriptors. We demonstrate the potential effects of these biases on our ability to effectively characterize catchments and identify functional similarity of catchment behavior with illustrative examples. Finally, we suggest possible ways to derive more robust, comprehensive and hydrologically meaningful catchment descriptors.

Outline

1. Introduction

Catchment descriptors are widely used metrics in the Earth and environmental sciences to describe various functional and structural aspects of hydrological catchments. The first definition of catchment descriptors was provided by Horton (1932) who defined them as "hydrological factors that relate specially to conditions dependent on the operation of the hydrological cycle, particularly to runoff and groundwater and maybe broadly classified as morphologic, soil factors, geological-structural factors, vegetational and climatic factors". In this review, we use a somewhat broader definition of catchment descriptors as any characteristic that describes the control volume enclosed by the hydrologically-effective catchment boundary (Liu et al., 2020) from the top of the atmosphere through Earth's surface down to the bottom boundary of the active flow circulation (Condon et al., 2020) that (potentially) relates to the operation of the hydrologic cycle (Figure 1a). It should be noted that we do not include any variables derived from hydrological fluxes or states (e.g., baseflow index) that in fact are frequently considered as hydrological signatures of catchment behavior (McMillan, 2020).

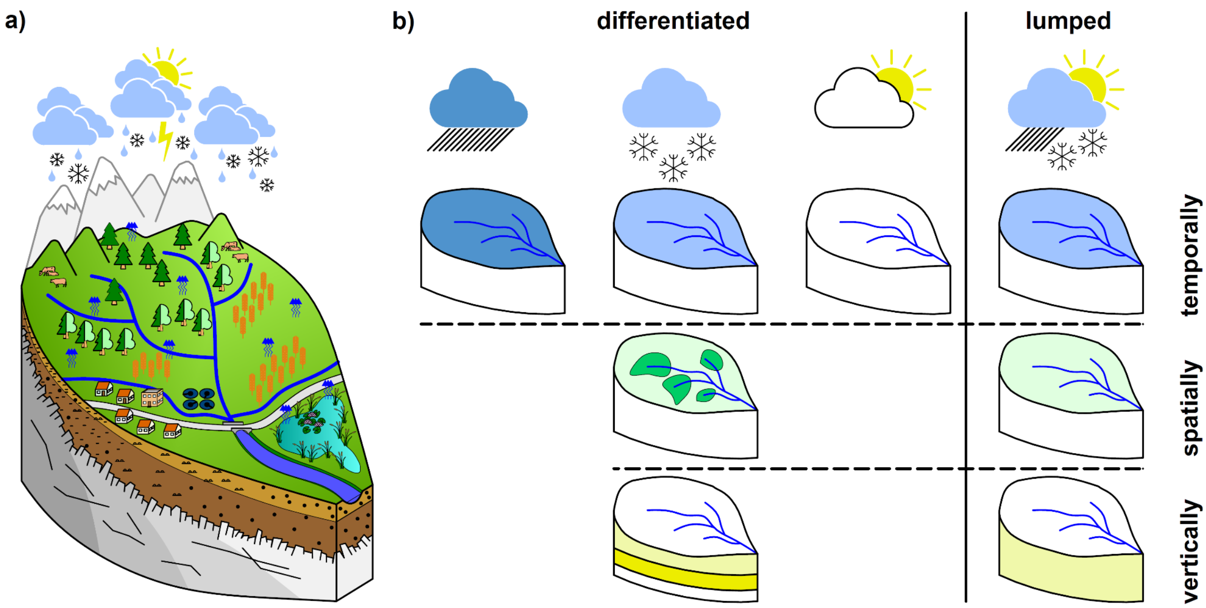

Figure 1 a) Elements of the terrestrial hydrological cycle with a catchment as a control unit (i.e., aggregation unit); **b)** aggregation practices: temporally-, spatially- and vertically-lumped or -differentiated approaches

Catchment descriptors provide useful insights into similarity of catchment structure and are widely used to classify catchments into homogeneous groups (Wagener et al., 2007; Sawicz et al., 2011; Merz et al., 2020b). Correspondingly, they are often instrumental in transferring information about catchment functioning (i.e., streamflow behavior, water quality metrics) from gauged to ungauged locations (Blöschl et al., 2013; Hrachowitz et al., 2013). Most importantly, catchment descriptors are key for generalization and transferability of local findings to other places and larger spatial scales, and they facilitate the search for hydrological regularities (i.e., patterns that explain the variability of catchment response). However, there are concerns that structural similarity of catchments as described by their current descriptors does not necessarily translate into similarity in hydrological behavior (Oudin et al., 2010; Tarasova et al., 2018).

Catchment descriptors are typically obtained by aggregating geospatial datasets such as digital elevation models or land use maps into a scalar value (Figure 1b). However, neither agreement nor guidelines exist in the scientific community on how descriptors should be selected, aggregated or evaluated (Addor et al., 2020). To date, there has been only one review on the frequency of selection of different catchment descriptors by Ssegane et al. (2012a) based on 42 non-systematically selected articles that provided rather limited insight on the matter. Additionally, Benson and Carter (1973) and Kiang et al. (2013) have provided summaries of regression-based regionalization studies from the reports of the US Geological Survey (USGS). They found that catchment area is almost always included as explanatory variable regardless of the streamflow-based target estimate (e.g., mean annual streamflow, flood quantiles, low flow quantiles). They also indicate that mean elevation, slope, precipitation, forest, water and impervious cover, as well as soil permeability are used often in the regionalization regression equations. Instead, other soil characteristics, land use and geological indicators are used less frequently in the reports of the USGS, although the regional water authorities are encouraged to add such information when possible (Farmer et al., 2021).

However, the large sample comparison of regionalization studies showed that methods based on spatial proximity still often outperform methods based on hydrological similarity (i.e., catchment descriptors, Parajka et al., 2013), suggesting that there is a substantial potential for improving how we characterize catchments and define their similarity. More problematically, little is known about the existence of potential biases and legacies in the characterization of catchments across different hydrology-related research disciplines and how they affect our understanding of hydrological similarity. Therefore, the main objective of this systematic review is to identify current practices, biases and limitations in catchment characterization particularly regarding the data sources and methods that are used for derivation and aggregation of descriptors. Specifically, we examine the following research questions:

A. What are the most popular data sources to derive catchment descriptors and are there any differences in their usage among different geographical regions and research fields?

B. How are catchment descriptors aggregated at the catchment scale and what aspects of internal variability are considered?

C. How, if at all, is the usefulness and uncertainty in different catchment descriptors quantified and evaluated?

We illustrate the potential effect of biases identified in the systematic review (Section 3) with selected examples (Section 4), and further suggest possible ways forward towards more reliable and comprehensive catchment descriptors (Section 5).

2. Methods

2.1 Selection of the research articles

We attempted to extract the most complete sample of research articles that include analyses of catchment descriptors of water bodies for various applications in Earth, environmental and hydrological sciences.

To achieve this aim, we followed current PRISMA guidelines for systematic reviews (Page et al., 2021) and extracted all journal articles written in English language indexed in Scopus resulting from the combination of search words "*catchmen*t" (or alternative terms such as "*watershed*", "*drainage basin*", and "*river basin*") and "*descriptor*" (or alternative terms such as "*characteristic*", "*attribute*", "*indicator*" and "*property*") in the title, abstract or keywords. Note that the search was conducted in a singular form (i.e., "*descriptor*" instead of "*descriptors*") to automatically account for both cases. The search for term "*property*" was conducted for the term "*propert*" to account for differences in spelling between singular and plural forms. Only cases where the term "*catchment*" or its equivalents mentioned above were preceding the term "*descriptor*" and its equivalents were considered (i.e., we used the operator PRE/1 to conduct the search). This initial search resulted in 2,659 articles (Table S1). The search was performed in October 2021.

For cases where no DOI identifier was available, the articles with any important information missing (i.e., author name or article title or both) that prevented us from finding the full text of the article, were excluded. In the next step, we excluded all repetitions by discarding all articles with identical titles. We further filtered out all articles that were not associated with catchments of any hydrological system (i.e., river, stream, lake or reservoir). As our main goal is to investigate practices in comparative analyses, we only selected research articles that investigate at least two catchments and not only mention catchment characterization but actually perform formal analyses (either quantitative or qualitative) of catchment descriptors. This selection resulted in 742 articles published in the period from 1967 to 2021 (Table S1).

2.2 Creating metadata for the final sample of articles

For each article we extracted the following information: year of publication, journal, country of study area, numbers of analyzed catchments and of analyzed catchment descriptors (Table S2).

All articles were categorized according to the **type of study** (i.e., data-based analysis, hydrological modeling, statistical or machine learning modeling and field studies) and by **type of application** (i.e., descriptive site comparison, catchment clustering/classification, quantitative control identification and regionalization) in their respective **research field** (i.e., water quality, water quantity, sediment transport, tracers, lake research, aquatic ecosystems) (Figure S1). We also recorded the **method used in each study to evaluate the "usefulness" of descriptors** for a corresponding goal of the study, i.e., explanatory power (e.g., bi-correlation), fit (e.g., multiple regression), predictive potential (e.g., performance of models based on catchment descriptors for test/validation samples), classification similarity (e.g., similarity of cluster memberships based on investigated catchment descriptors and tested using hydrological variables/signatures), or significance in the differences between the resulting groups of catchments.

2.3 Detailed analysis of individual data sources and catchment descriptors

We organized all catchment descriptors according to the following **original data sources** from which they are customarily derived (Table S2):

1. hydrometeorological time series
2. digital elevation models and topographical maps
3. remotely sensed vegetation and land use / land cover maps
4. maps of anthropogenic presence (e.g., population and infrastructure maps)
5. derived hydrogeological maps (e.g., maps of aquifer types or corresponding hydraulic conductivity derived from litho-stratigraphic maps using assumptions on the permeability/consolidation properties of different litho-stratigraphic units)
6. lithological and litho-stratigraphic maps
7. soil depth maps and soil texture maps (including soil hydraulic properties that can be derived from soil textures e.g., using pedo-transfer functions, such as, saturated conductivity, field capacity etc.).
8. soil type maps

Catchment descriptors that are derived using a combination of two or more different data sources (e.g., soil topographic index) were assembled into a separate composite group (Table S2, *Composite*) and analyzed separately (see Section 3.2).

For each individual descriptor, organized according to main data sources, we identified **variable type** (i.e., binary, continuous, discrete, nominal, ordinal) and **typical aggregation metrics** (e.g., mean/median, mode, range, coefficient of variation, skewness, standard deviation, portion of catchment covered by the descriptor, etc.). Based on that information, we distinguished whether the studies use **spatially-, vertically- and temporally-differentiated or -lumped** aggregation approaches (Figure 1b). We consider any variable that is aggregated in a way that includes or represents a measure of distance in space, captures spatial variability in space or represents class or category that implies spatial distance or spatial distribution, as a spatially-differentiated variable. For example, the mean value of elevation averaged for the whole catchment is an example of spatially-lumped aggregation, while coefficient of variation of elevation within the catchment is an example of spatially-differentiated aggregation. Similarly, we consider any variable aggregated to capture temporal variability, seasonality, duration, timing or frequency of occurrence of the phenomena, as a temporally-differentiated variable. For example, mean annual precipitation is an example of a temporally-lumped aggregation, while seasonality of precipitation is considered as temporally-differentiated aggregation. We consider any variable which is aggregated to represent vertical subsurface and surface variability or which represents a class or category that implies vertical distance or vertical distribution, as a vertically-differentiated variable. For example, mean clay content in the whole soil column can be considered as vertically-lumped aggregation, while mean clay content in the topsoil or in the subsoil can be considered as vertically-differentiated aggregation.

3. Results

3.1 Summary of the obtained sample of articles

In the obtained sample of articles more than 50% of the analyzed studies focus on various aspects of water quantity (e.g., hydrological signatures, flood characteristics) (Figure 2a). Around 25% of all articles focus on water quality (e.g., concentrations of different chemical compounds, concentration-discharge relationships). The remaining 25% of studies focus on aquatic ecosystems (e.g., diversity of species, abundance of different traits), lake research, sediment transport and tracers (e.g., mean transit times, water ages) (Figure 2a).

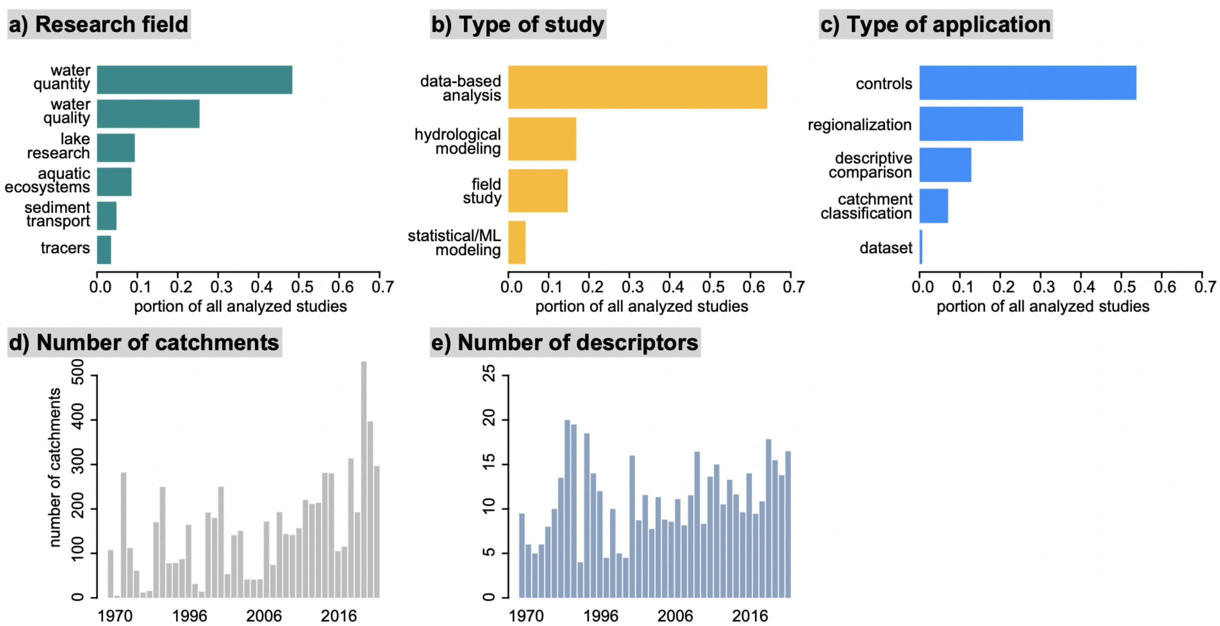

Figure 2 Thematic summary of analyzed articles for **a)** different research fields, **b)** type of studies and **c)** types of application; **d)** temporal distribution of mean number of catchments analyzed in reviewed articles per year; **e)** temporal distribution of mean number of catchment descriptors analyzed in reviewed articles.

Most of the examined studies perform a data-based analysis (i.e., investigate the empirical dependencies and relations between catchment descriptors and target variables). Only 5% of all studies focus on statistical modeling (e.g., modeling of flood frequency curves) or modeling of streamflow using machine learning approaches (Figure 2b). Around 15% of all studies are focused on hydrological modeling. The remaining 15% of articles are field studies that actively obtain new measurements of the target variables.

More than half of all studies attempt to identify dominant controls for a target variable among the considered catchment descriptors and almost 30% of studies use catchment descriptors for regionalization purposes. Around 15% of all studies employ catchment descriptors for a descriptive (i.e., qualitative) comparison between catchments (Figure 2c).

3.2 Summary of variables derived from individual data sources

Among surface properties, descriptors extracted from digital elevation models and hydrometeorological datasets are mostly continuous variables, while descriptors of vegetation and land use are mostly nominal (Figure S2a). The descriptors extracted from digital elevation models are usually extracted without any aggregation (i.e., scalar values such as catchment area or centroid location) or as a mean value (e.g., mean elevation or mean slope) and portion of catchment covered (e.g., portion of catchment covered by certain landforms such valley bottoms or hillslopes). The vast majority of descriptors from hydrometeorological datasets are aggregated as mean values (Figure S2b). The descriptors of vegetation cover and land use are mostly aggregated as a portion of catchment or portion of the riparian area covered by a certain class (e.g., agriculture or forest) (Figure S2b). Instead, the descriptors of anthropogenic activities are very diverse and are extracted equally often as nominal, continuous or discrete variables (Figure S2) and correspondingly aggregated as portion of catchments covered by a certain category (e.g., different types of roads), mean values and sums (e.g., livestock density).

Among subsurface properties, apart from soil depth and texture maps, nominal variables prevail (Figure 3a). For derived hydrogeological maps also ordinal information (e.g., ordered categories of hydraulic conductivity of the subsurface) is common. Correspondingly, subsurface properties derived from hydrogeological, litho-stratigraphic and soil type maps are usually aggregated as fraction of catchment covered by the corresponding nominal or ordinal category, or even simply as a binary presence or absence of a given category (Figure S3b). The maps of soil depth and texture that usually include soil hydraulic properties (conductivity, field capacity, available water content) equally frequently provide continuous and nominal information (e.g., volumetric clay content, porosity, depth to bedrock) and are correspondingly aggregated as spatial mean values or portions of catchment covered by a certain category (e.g., portion of catchment covered by sandy soils) (Figure S3).

We identified several attempts to derive composite catchment descriptors by combining different data sources. However, it seems that such descriptors are used only singularly with the exception of soil topographic index (a combination of soil hydraulic conductivity and the topographic wetness index, Walter et al., 2002) and Soil Conservation Service curve number that combines the information on soil type, land use and surface cover of the catchments (Mishra and Singh, 2003; see Table S2, *Composite*). It is worth noting that in absolute terms even soil topographic index and curve number are used very infrequently compared to the non-composite descriptors.

3.3 Identified biases in current practices of catchment characterization

3.3.1 Bias 1: Dry environments are underrepresented

We find large differences in the number of studies analyzing catchment descriptors that are published in different countries (i.e., according to the location of the study area, Figure 3). We extracted the aridity index (i.e., ratio of precipitation and potential evaporation) for each country using the dataset of Zomer et al. (2022) and the dominant climatic zone using the dataset of Beck et al. (2018). Our analysis shows clear disproportions in the focus of study areas of the analyzed articles and the global land surface (Figure 3b, c). Although temperate climates account globally only for about 10% of land surface (Beck et al., 2018), almost 25% of study areas are associated with these regions. On the contrary, less than 5% of all articles focus on the tropical areas, despite their global proportion of 16% (Figure 3b). The discrepancies are even more pronounced in terms of representation of wet and dry environments. The research on catchment characterization to date disproportionally focuses on wet environments (energy-limited environments, i.e., aridity index more than 1) despite their marginal fraction in global land surface cover (Figure 3c). Instead, even if 42% of global land surface area corresponds to semi-arid, arid and hyper-arid conditions (aridity index is less than 0.5, i.e., potential evaporation is twice the amount of precipitation; Zomer et al., 2022), only 16% of all studies focus on such dry environments (Figure 3c).

The observed discrepancy might be driven by scarce observation networks in drier and warmer environments (Cho et al., 2017; Krabbenhoft et al., 2022). There are substantial differences in the anthropogenic use of surface waters in wet and dry environments (i.e., navigation, industrial and drinking water abstraction, fishery, recreation, etc.) that might have led to emergence of the extensive monitoring networks of the perennial streams in wetter environments to support reliable water resources management for different users. Moreover, in drier environments non-perennial streams are more common, but the attempts to gauge them are still scant (Messager et al., 2021), possibly adding to the observed disproportionality of catchment characterization studies.

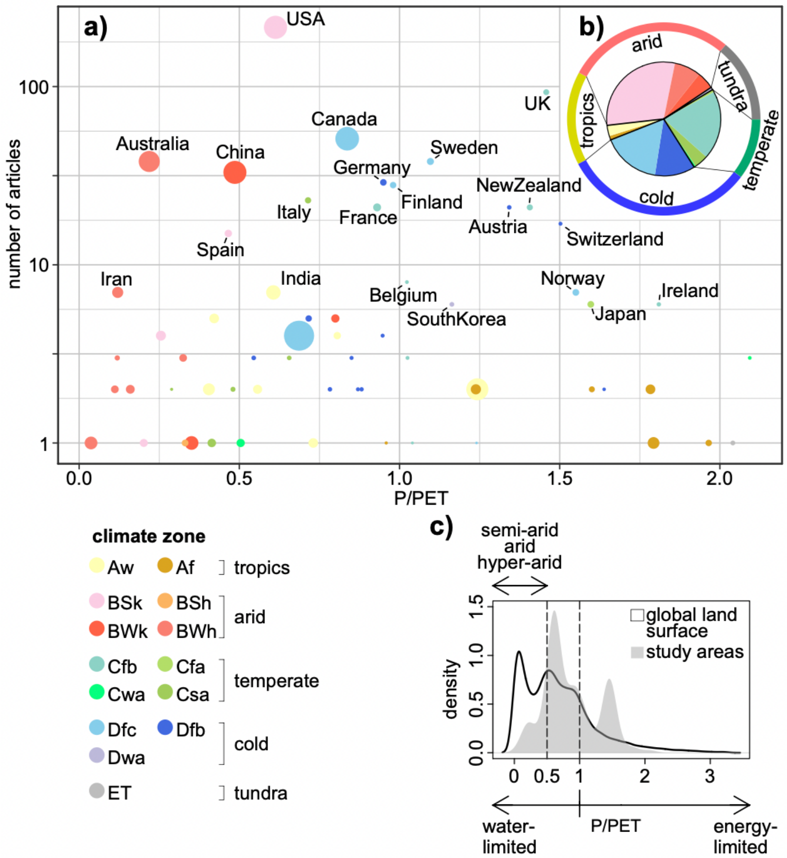

Figure 3 Discrepancy between the study areas of articles on catchment characterization and distribution of global land surfaces. **a)** The number of studies on catchment descriptors among energy-limited and water-limited environments (defined by mean aridity index that is a ratio of precipitation (P) and potential evaporation (PET)) of the country where the study area is located from Zomer et al (2022)). The y axis is in log scale. The size of the points is proportional to the size of corresponding countries. Color-coding of points corresponds to the climate zone dominant in the corresponding country according to the Köppen-Geiger classification from Beck et al (2018) (Af: Tropical rainforest; Aw: Tropical savannah; BSh: Arid steppe hot; BSk: Arid steppe cold; BWh: Arid desert hot; BWk: Arid desert cold; Cfa: Temperate without dry season hot summer; Cfb: Temperate without dry season warm summer; Csa: Temperate dry hot summer; Cwa: Temperate dry winter hot summer; Dfb: Cold without dry season warm summer; Dfc: Cold without dry season cold summer; Dwa: Cold dry winter hot summer; ET: Tundra). **b)** The proportion of articles attributed to different climate zones (inner circle) and the proportion of these climate zones in the global land surface area (outer circle). **c)** The distribution of aridity index of the study areas in the analyzed articles and the distribution of aridity index of the global land surface based on the dataset of Zomer et al. (2022). Values of aridity index above 1 correspond to energy-limited regions and values below 1 correspond to water-limited regions. Values of aridity index below 0.5 correspond to dry semi-arid, arid and hyper-arid environments.

Regardless of the complexity of the socio-economic drivers that have led to the discrepancies between the density of observation networks in wet and dry environments, these discrepancies are likely to create a bias in our perception of the importance of different catchment descriptors for capturing functionality of hydrological systems. Since studies in dry environments are underrepresented in our analysis, it is difficult to judge if current descriptors are as useful in such regions. This possibly has already contributed to lower prediction accuracy of regionalization methods based on physical similarity (i.e., methods that use catchment descriptors as the measure of similarity between gauged and ungauged catchments) in dry environments (Parajka et al., 2013; Salinas et al., 2013; Blöschl et al., 2013).

3.3.2 Bias 2: Subsurface properties are underrepresented

Our systematic review shows large disproportionality in the usage of different data sources/datasets for the derivation of catchment descriptors (Figure 4). The datasets describing surface properties such as digital elevation models, hydrometeorological datasets, land use or land cover maps are used much more frequently than data sources describing subsurface properties such as soil type, texture or depth maps, lithological and hydrogeological maps.

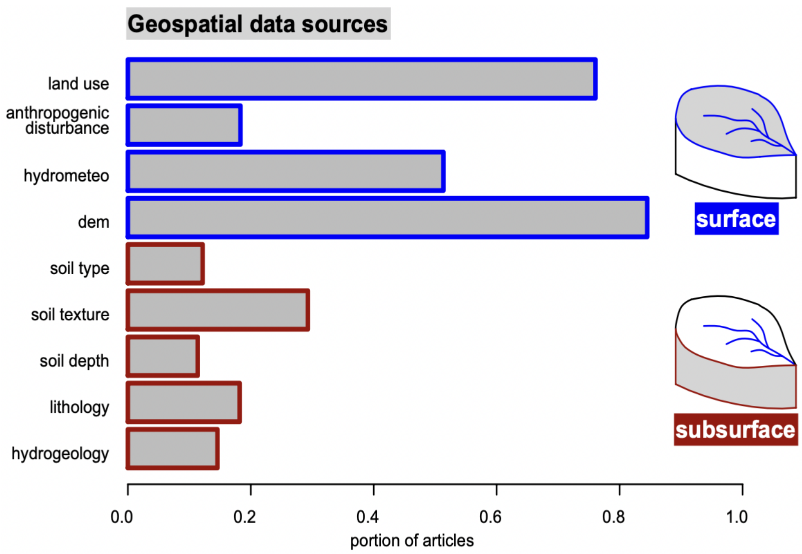

Figure 4 Portion of articles that include descriptors (at least one) from different data sources that represent surface properties (blue outline): digital elevation models or topographical maps (*dem*), hydrometeorological series (*hydrometeo*), maps of anthropogenic disturbance and land use; and subsurface properties (dark red outline): hydrogeological maps, lithological maps, soil depth maps, soil texture maps and soil type maps.

The most frequent data sources are digital elevation models (ca. 85% of all studies derive at least one catchment descriptor from this source), which is not surprising as digital elevation models with high spatial resolution (compared to other data sources) are currently available globally (e.g., 90 m from SRTM mission, 30 m from ASTER GDEM), with even higher resolution (<10m) LIDAR data becoming increasingly accessible locally (Hawker et al., 2018). However, even prior to the age of global high quality datasets (i.e., the beginning of 2000s), corresponding descriptors were widely used (Figure S4). Land use, land cover and vegetation maps also belong to one of the most popular sources with almost 80% of all analyzed studies deriving at least one descriptor from these sources. Similarly to digital elevation models, there are several high resolution global and regional land use and land cover products available (e.g., GLC2000, EarthStat, CORINE). Around 50% of all studies used at least one descriptor derived from hydrometeorological datasets such as precipitation, temperature, evaporation time series or rasters (Figure 4). Less intense usage of hydrometeorological variables compared to land use properties might be related to the fact that at least several years of observations are required to derive corresponding long-term properties. In contrast to other surface descriptors, anthropogenic disturbances are only used in 20% of all studies (Figure 4). They have become more abundant in recent years (Figure S4), likely related to the growing availability of corresponding data sources and an awareness of the importance of human activities on catchment functioning in the scientific community (Wagener et al., 2010; Sivapalan et al., 2012).

Data sources containing information regarding subsurface properties of catchments are much less abundant compared to those of surface properties (Figure 4). It is also interesting to note that there are little differences in the practices of different research areas, types of studies and applications (Figure S7-S9), indicating a consistent underrepresentation of subsurface properties in catchment characterization studies. Soil texture maps (that also include derived soil hydraulic properties) are the most frequently used data source among subsurface properties (almost 30% of all studies). Despite Food and Agriculture Organization (FAO) efforts on providing global soil maps as early as the 1980s (FAO, 2006), the frequency of usage of soil types did not increase with time (Figure S5). Instead, there is a pronounced increase in the usage of soil texture data (Figure S5) that corresponds well to the development of soil digital mapping in the 2000s (Minasny and McBratney, 2016). Infrequent inclusion of lithological and hydrogeological descriptors (ca. 20%) might be related to the limited availability of high-quality local and regional hydrogeological and lithological data sources (Figure S6). Moreover, despite the emergence of global lithological products (e.g., GLiM, Hartmann and Moosdorf, 2012) from the 2010s onwards, we did not detect an increase in the usage of the corresponding descriptors (Figure S5), indicating that the coarse resolution and the uncertainties of global products might still be hampering characterization of the deeper subsurface (Gleeson et al., 2021).

3.3.3 Bias 3: Negligence of spatially- and vertically-differentiated catchment descriptors

Our analysis of aggregation methods for estimating catchment descriptors showed that the majority of descriptors are aggregated in a lumped fashion (i.e., not considering temporal, spatial or vertical variability of descriptors within catchments) (Figure 5). However, temporally-differentiated aggregation is used in more than 30% of all cases for aggregation of descriptors from hydrometeorological datasets (e.g., descriptors that capture seasonality of precipitation, temperature, snow cover or their temporal variability, such as temporal coefficient of variation or standard deviations). Temporally-differentiated aggregation is uncommon for other data sources as they mostly provide static information (apart from temporal changes in land use and seasonal fluctuations of groundwater depth).

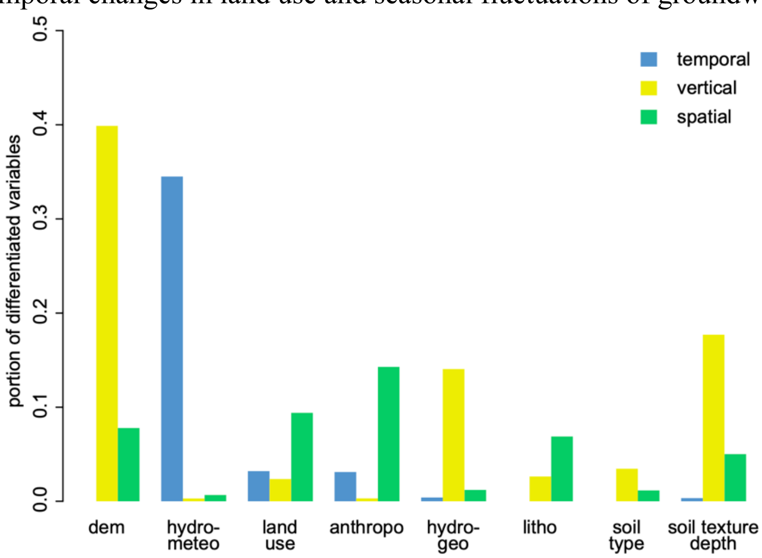

Figure 5 Portion of descriptors derived using different aggregation practices for each main data source (digital elevation models (*dem*), hydrometeorological series (*hydrometeo*), land use and land cover maps, maps of anthropogenic disturbance (*anthropo*), hydrogeological maps (*hydrogeo*), litho-stratigraphic maps (*litho*), soil type maps and soil texture and soil depth maps).

Vertically-differentiated descriptors are used to capture variability of a given property with depth (i.e., for subsurface properties) or with elevation (i.e., for surface properties). Almost 40% of all descriptors derived from digital elevation models (e.g., portion of catchment above a certain elevation) and around 20% soil depth and texture descriptors (e.g., fraction of sand in top- and subsoils) are vertically-differentiated (Figure 5). By contrast, there are much fewer descriptors derived from hydrogeological or lithological maps that reflect on vertical structures of catchments (e.g., differences between dominant surficial and bedrock geology or location of impermeable layers). It is worth to note that the lack of vertically-differentiated descriptors for hydrogeological and lithological maps is likely related to the limited availability of high-quality information about these properties compared to e.g., digital elevation models.

Surprisingly, spatially-differentiated aggregation (e.g., spatial coefficient of variation or standard deviation) is rarely used to derive descriptors from examined data sources (Figure 5) despite availability of high-resolution gridded products for surface data sources (e.g., less than 10% of all descriptors derived for digital elevation models and land use are spatially-differentiated). Even more surprisingly, despite numerous attempts for temporally-differentiated aggregation of descriptors from hydrometeorological datasets, there are almost no spatially-differentiated descriptors (e.g., spatial coefficient of variation or skewness of aridity index within the catchment) derived despite an increasing abundance of high-resolution hydrometeorological gridded datasets.

These aggregation practices are generally consistent among different research fields (Figure S10). Spatially-differentiated aggregation of land use and lithological data is slightly more common in the water quality field (almost 20% of studies) compared with all other fields. Instead, spatially-differentiated aggregation of descriptors (e.g., distribution of agricultural areas within the catchment or their proximity to the river network or outlet) is rather rare in lake, aquatic ecosystems, sediment transport and tracer research fields (Figure S10). Interestingly, we do not see any changes in the current prevalence of lumped aggregation practices even in more recent studies published after 2010 and after 2015 (Figure S11) when high resolution geospatial datasets become increasingly abundant.

3.3.4 Bias 4: Lack of evaluation of usefulness and uncertainty analysis of catchment descriptors

Most of the examined studies (almost 40%) evaluate usefulness of catchment descriptors by examining their explanatory power, usually using simple bi-correlation analysis (Figure 6). However, almost 25% of all studies do not perform any quantitative evaluation (i.e., catchment descriptors are selected subjectively based on the authors' perception on the usefulness of catchment descriptors without actually evaluating it quantitatively) and apply descriptors directly for e.g., comparison between study sites or regionalization. This seems to be especially the case in the water quantity research field where almost 35% of all articles do not perform any evaluation (Figure S12). Overall, less than 10% of all studies perform out-of-sample cross-validation by examining the predictive potential of different catchment descriptors or their combinations.

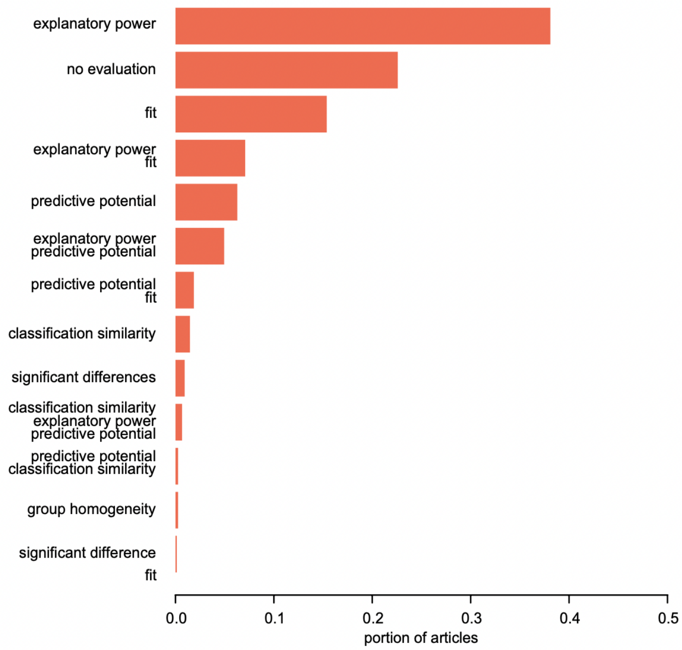

Figure 6 Portion of articles considering different approaches for evaluation of usefulness of catchment descriptors for the purpose of the given study.

Interestingly, a lack of cross-validation can be observed among all research fields (Figure S12) and we find little evidence that the number of attempts to evaluate catchment descriptors more rigorously increases (Figure S13). This finding is especially worrisome since we observe an increase in the number of considered catchment descriptors (from 9.6 to 13 descriptors on average per article in the last three decades) indicating a potential increase in multicollinearity issues and catchments (from 124 to 267 catchments on average per article in the last three decades) potentially indicating increase in the sample size for a cross-validation analysis (Figure 2d, e).

There are several uncertainty sources that might be relevant for deriving and using catchment descriptors ranging from the choice of the data source product (e.g., different precipitation products, different digital elevation models), resolution of these products, to the uncertainty of the choice of aggregation method. Among analyzed articles we did not encounter any comprehensive attempts to perform uncertainty analyses of derived catchment descriptors, although there is increasingly more information available on the intrinsic uncertainties of the products and increasingly more alternative products available for the same data source (Addor et al., 2020). This might indicate a persistent subjectivity in the choice of catchment descriptors used for analysis that can result in a biased perception of their usefulness.

4. Discussion

Our systematic analysis has identified four crucial biases in current practices of catchment characterization (Section 3): 1) underrepresentation of dry areas; 2) underrepresentation of subsurface properties; 3) negligence of differentiated aggregation and 4) lack of cross-validation-based evaluation and uncertainty analysis of catchment descriptors. In this section we use several examples to detail ingredients currently missing in catchment characterization and to demonstrate how identified biases might affect the effectiveness of catchment characterization.

4.1 Missing ingredients of catchment characterization in dry environments

Water-limited environments are often associated with pronounced threshold behavior and high spatial heterogeneity (Rodriguez-Caballero et al., 2014; Jiang et al., 2023). In contrast to energy-limited environments, spatial variability and spatial dynamics of precipitation (Puigdefabregas et al., 1999; Morin et al., 2006), regional groundwater flow (Fan, 2019; Gordon et al., 2022), evapotranspiration and substantial water loss to the subsurface (Liu et al., 2020), as well as surface and subsurface water interactions in the hyporheic zone of losing ephemeral streams (Kampf et al., 2016) might play a crucial role, indicating that potentially different descriptors might be needed to effectively represent the functioning of water-limited hydrological systems. A considerable body of empirical regionalization studies indicates that **different descriptors are relevant in dry and wet environments (**Turnipseed and Ries, 2006; Stein et al., 2021**)**. Moreover, the differences in hydrological processes of dry and wet environments (Dunne, 1978; Li et al., 2014) call also for different catchment descriptors to characterize these contrasting domains.

Particularly, in arid environments, **surface cover properties** (i.e., rock vs soil cover) might have a more important role for runoff generation processes compared to climatic drivers (Yair and Kossovsky, 2002; Kampf et al., 2018), since the presence of stone cover considerably affects infiltration rates (Abrahams and Parsons, 1991). Estimation of hydraulic conductivity is especially challenging in semi-arid regions where **crusting and sealing of soils** plays an important role (Becker et al., 2018). In such regions remote sensing data of the surface of soils may be a much more accurate proxy of hydraulic conductivity than estimates from pedo-transfer functions (Becker et al., 2018). **The age of desert pavements** (also referred as stone pavements and reg soils; Springer, 1958), which are one or two layers of closely packed clasts embedded in fine-grained soil horizon, might also play an important role in runoff generation processes in arid and hyper-arid environments (McFadden et al., 1987). Older desert pavements are associated with lower infiltration capacity (Wells et al., 1985), while older and more structured soils under the desert pavement have lower hydraulic conductivity than younger soils (Meadows et al., 2008). Moreover, biological soil crusts (that are complex communities of cyanobacteria, algae, fungi, bryophytes and lichens, Figure 7) might be another factor modulating surface infiltration capacity in the non-vegetated areas (Rodriguez-Caballero et al., 2014; Marchamalo et al., 2016). Therefore, further investigation on the spatial distribution of **crusted and uncrusted soil surfaces** might be beneficial for understanding runoff generation processes in dry environments (Wei et al., 2015; Kampf et al., 2018). Finally, **soil laterization,** a weathering process that includes chemical transformation of soils, is typical in tropical and subtropical environments with prolonged dry period, but its potential effect on recharge processes is still poorly understood (West et al., 2022).

In dry environments where pedogenic processes are slow, vegetation plays a very important role in modulating surface infiltration rates (Caldwell et al., 2012). Thompson et al (2010) showed that biomass plays a critical role for infiltration in a wide range of water-limited environments, potentially even outweighing the importance of soil types. The studies of Puigdefabregas et al. (1999), Lesschen et al. (2009) and Marchamalo et al. (2016) also provide evidence that spatial distribution of vegetation patches (Figure 7) and location of terraces define hydrological connectivity and control sediment transport in dry environments. For example, infiltration occurs more commonly near vegetation patches compared to barren areas (Lesschen et al., 2009). Moreover, encroachment of woody vegetation in arid and semi-arid environments, despite their very limited absolute land cover area, might have a considerable effect on the occurrence of surface (Pierini et al., 2015) and subsurface storm flow (Wilcox et al., 2008), indicating that particular attention should be given to the characterization of the structure of the **vegetation cover** in dry environments.

In arid environments where non-perennial streams prevail (Messager et al., 2021), the flow through the streambed alluvium might also play an important role (Kampf et al., 2016), indicating that the **streambed texture** might be an important descriptor as well.

Finally, arid and semi-arid environments are characterized by **high spatial variability of rainfall** (Goodrich et al., 1995) and there is substantial evidence that indicates the imperative role of spatial structure of rainfall and its propagation within the catchment for the corresponding runoff response (Syed et al., 2003; Morin et al., 2006). The gradient of annual rainfall variability is very steep in arid environments leading to disparate catchment responses even at very small scales (Belachsen et al., 2017), suggesting that our common spatially-lumped aggregation techniques might be especially ill-suited in such environments. Since runoff generation in dry environments is mostly related to infiltration excess (Dunne, 1978), it is extremely important to accurately characterize the areas with high rainfall intensities and capture its spatiotemporal variability (Yakir and Morin, 2011). Such strong spatial variability of hydrological cycle components and concurrent sparse observational networks might also lead to increased uncertainty of catchment descriptors in dry environments (e.g., Gordon et al., 2022).

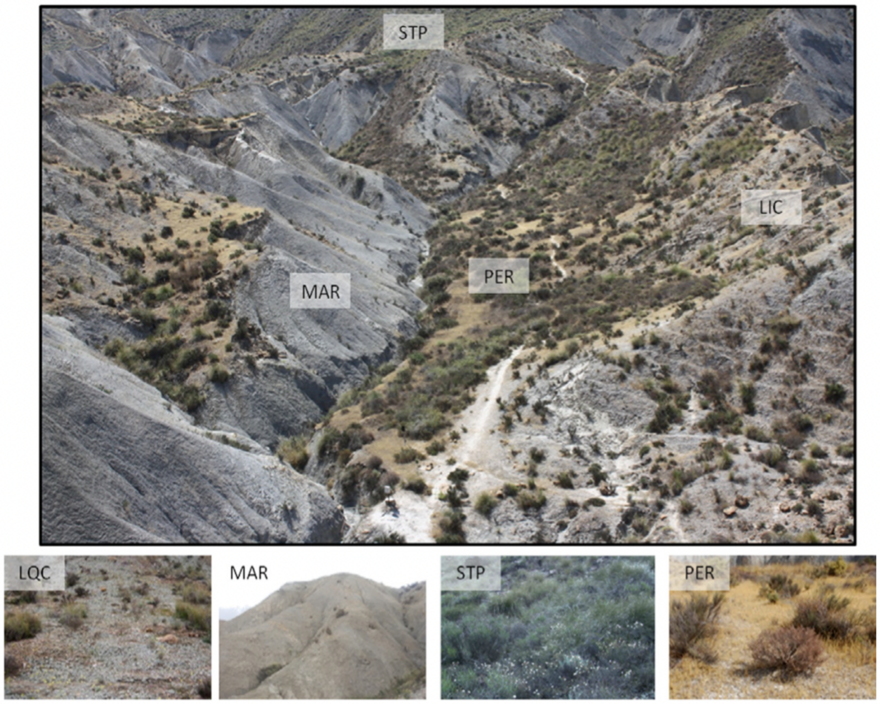

Figure 7 Semi-arid El Cautivo catchment (Spain) demonstrating the variety of surface covers in dry environments: LQC – lichen-dominated hillslopes; MAR – bare soil physically crusted; STP – vegetation downstream lichen hillslopes; PER – headwaters dominated by high perennial herbs. From Rodriguez-Caballero et al. (2014) with permissions from Elsevier.

4.2 Missing ingredients for characterizing the subsurface

In contrast to dry environments, subsurface flow is largely the dominant mechanism of runoff generation in temperate climates (Hewlett and Hibbert, 1967). However, we find that in current catchment characterization subsurface properties are largely underrepresented (Figure 4) and seldom aggregated in a spatially- or vertically-differentiated manner (Figure 6). Moreover, currently used descriptors might not necessarily be representative of hydrological dynamics of catchments. Although information about the type of the unweathered bedrock is often available (e.g., Hartmann and Moosdorf, 2012), it might not always be useful without information on the **geomorphic setting.** For example, the presence and the thickness of sedimentary deposits and intact regolith (weathered bedrock) are crucial for hydrological and biogeochemical responses of landscapes (Pelletier, et al., 2016), and the former are particularly important in depositional regions, such as alluvial planes and post-glacial landscapes (Gleeson et al., 2014). Such information on **unconsolidated sediments** was recently added to the global lithological and subsurface permeability maps (Börker et al., 2018; Huscroft et al., 2018), but as our analysis showed is still rarely used in catchment characterization studies. Moreover, the information on the **depth of weathered or fractured bedrock** remains scarce or very uncertain, especially at the large scales, although a growing body of studies provides evidence on the importance of rock moisture (McCormick et al., 2021) and deep groundwater circulation (Fujimoto et al., 2016; Somers and McKenzie, 2020) for hydrological and biogeochemical cycles (Figure 8). Not only the thickness, but also the orientation of the aquifer bottom and its (dis)similarity to surface topography determines the direction of the regional groundwater flow and defines the presence of the inter-catchment groundwater flow (Liu et al., 2020). The latter might affect gaining and losing streamflow conditions (Fan, 2019) and alleviate or exacerbate the severity of streamflow droughts (Hellwig et al., 2022).

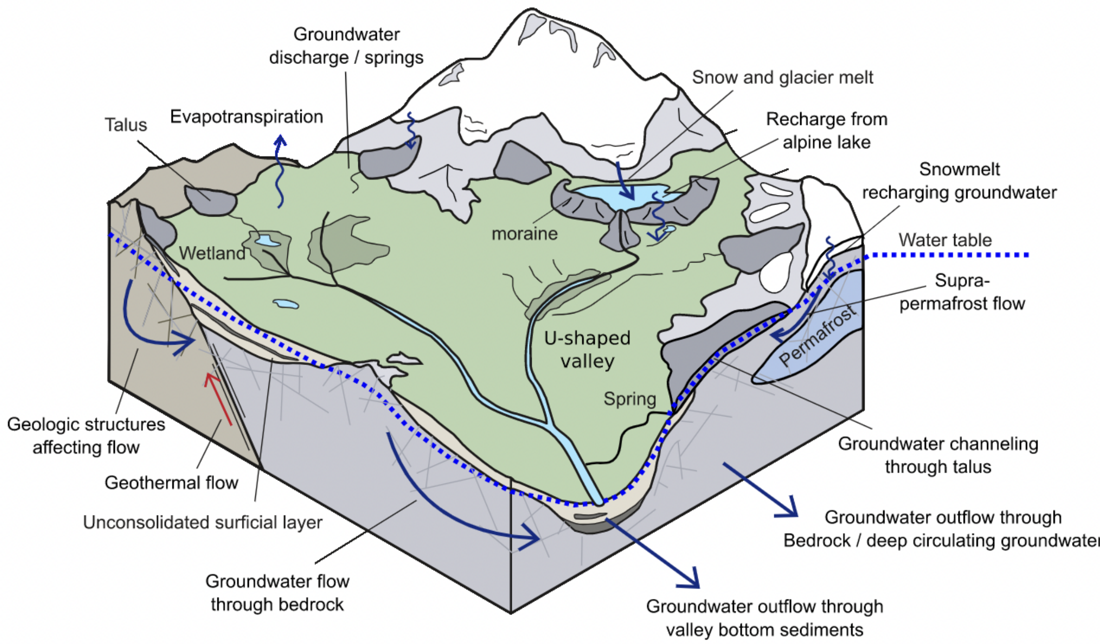

Figure 8 Perceptual model illustrating the complexity of high mountain hydrogeological processes including groundwater flow through subsurface features, such as talus slopes, moraines, valley bottom sediments, and bedrock, and the influence of permafrost and geological structures. From Somer and McKenzie (2020), CC-BY.

Another important aspect that is rarely considered in subsurface characterization of catchments is **secondary permeability** (i.e., the permeability developed in the rock after its deposition or emplacement). Scibeck et al. (2016) found, based on data from long tunnels, that 40-80% of all faults in crystalline rocks and 30-70% of all faults in sedimentary rock are highly permeable. Secondary permeability particularly impacts the behavior of karst systems, resulting in their considerable heterogeneity (Bakalowicz, 2005).The structure of karst systems and corresponding recharge vary strongly across climatic and topographic regions (Hartmann et al., 2015; Hartmann et al., 2017). However, although lithological maps often report the presence of karst or even more generally carbonate rocks, information on the **degree of karstification** is rarely available, leading to erroneous expectation about the similarity of hydrological response in catchments underlying by the same lithological class (Figure 9). The degree of karstification is related to the maturity of the karst, indicating that additional information on the geological age might provide useful insights for understanding the variability of response within karst regions (Gnann et al., 2021). The effect of **secondary permeability** might not only be relevant for carbonate rocks. Volcanic rocks might be associated with very different runoff generation processes as weathering gradually shapes surface drainage networks promoting fast flow components compared to highly permeable base flow-dominated younger landscapes (Jefferson et al., 2010). Metamorphic rocks can also have very contrasting hydraulic properties, simply because of differences in **orientation with respect to the surface topography** (Leone et al., 2020).

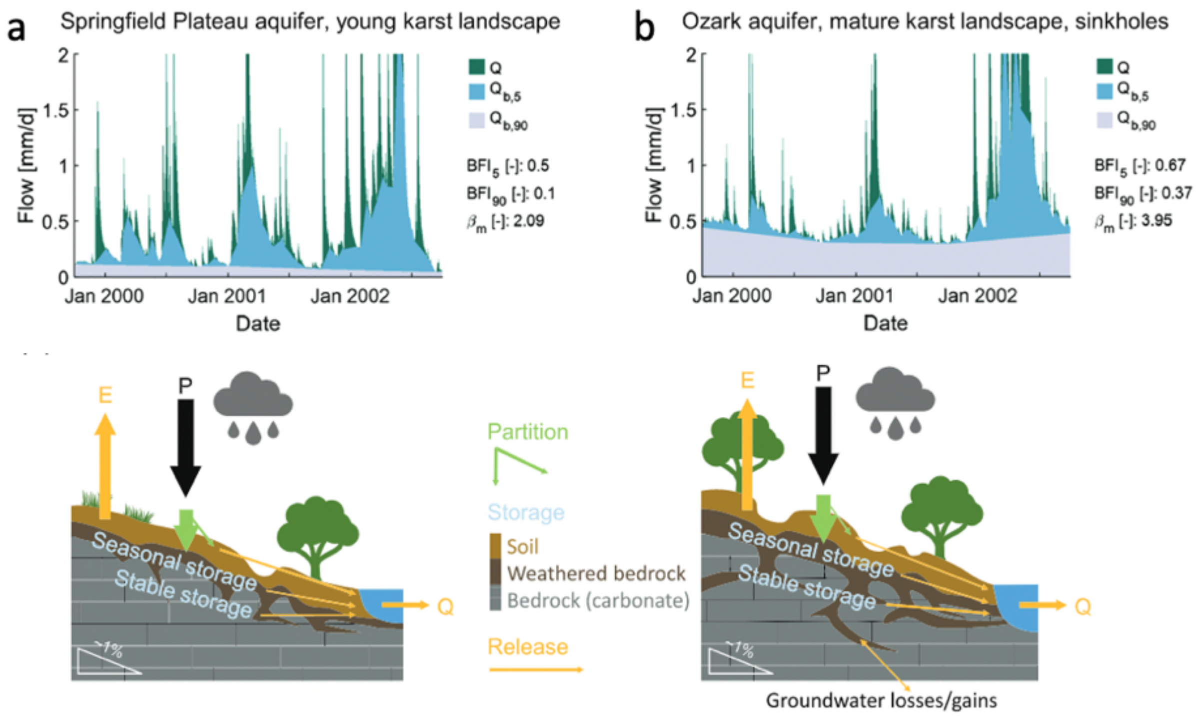

Figure 9 Contrasting hydrographs of two example catchments Turnback Creek above Greenfield (a) and Current River at Van Buren (b) and their corresponding perceptual models (bottom panel). The width of the arrows indicates the amount of water relative to a normalized precipitation input. This example illustrates considerable differences in the baseflow dynamics in two catchments located in the Ozarks (Missouri, USA), that despite proximity are underlain by carbonate rocks of different maturity. From Gnann et al. (2021) with permissions from American Geophysical Union.

Other potential obstacles for a comprehensive characterization of a catchments' subsurface are the methods that we currently use to **derive soil hydraulic properties** (e.g., saturated hydraulic conductivity). These methods rely on the extrapolation of soil attributes measured in a few local soil samples that might not be representative at larger (catchment to regional) scales (Gutmann and Small, 2007; Or, 2020). Additionally, hydrological functioning of soils might vary greatly depending on the soil structure (Gerke and van Genuchten, 1993) and might be strongly conditioned by biophysical activities (Jarvis et al., 2013) that are not considered in the pedo-transfer functions used to derive soil hydraulic properties (Fatichi et al., 2020; Bonetti et al., 2021). Current pedo-transfer functions rely heavily on soil texture information (Vereecken et al., 2010; Van Looy et al., 2017), although the variability of soil hydraulic properties within the same class might be even larger than between the classes (Gutmann and Small, 2007). These omissions indicate that huge uncertainties are likely to be inherent in the derived soil hydraulic properties (Paschalis et al., 2022) that we currently use for subsurface catchment characterization. Imposing multiple physical constraints that consider the effects of vegetation and soil structure on infiltration might improve state-of-the-art pedo-transfer functions and lead to a more accurate representation of soil hydrological processes at larger scale (Lehmann et al., 2020).

4.3 Missing ingredients of differentiated aggregation in catchment characterization

4.3.1 Vertical layering

The **vertical architecture of the critical zone** plays a crucial role for runoff generation processes and is not resolved in most of currently used descriptors. The **presence, discontinuity level** and particularly **the depth of impeding layers** have a crucial impact on hydrological response, well-documented in small research watersheds (e.g., Gannon et al., 2014; Zimmer and McGlynn, 2017) but also at the regional scale (Tarasova et al., 2018; Zimmer and Gannon, 2018). The presence of an impeding layer might limit the available catchment subsurface storage and lead to a flashier event runoff response (Zimmer and McGlyn, 2017; Tarasova et al., 2018). For example, Zimmer and Gannon (2018) showed that despite lowland topography, deeper critical zone and weathered bedrock, the baseflow of catchments in the Pennsylvanian Piedmont region are much more sensitive to precipitation variability than in the mountainous Appalachian region with shallow bedrock. This can be explained by the presence of a shallow and continuous impeding layer that considerably limits the available storage capacity and thus the capacity to buffer climate variability, making Piedmont catchments potentially more sensitive to climate change. **Bedrock topography,** particularly its difference from surface topography, might be another factor modulating runoff generation processes and the non-linearity of stormflow in temperate climates (Freer et al., 2002; Tromp-Van Meerveld and McDonnell, 2006). Defining the **depth of active flow** (or bottom of the catchment) is another important ingredient poorly featured in our current catchment characterization practices that is very important for understanding the contribution of deeper flow paths to catchment responses (Condon et al., 2020) and the variability of solute export patterns and legacy contaminations across different catchments (van Meter et al., 2017).

4.3.2 Spatial organization

In Section 3 we have identified a striking lack of spatially-differentiated descriptors (Figure 6). This is the case even for those surface properties that currently can easily be obtained from available high resolution gridded datasets. Nonetheless, spatial organization of the landscape forms within catchments might be crucial for shaping runoff generation processes (Loritz et al., 2019), while **spatial distribution** of land use plays a crucial role for shaping nutrient export patterns to adjacent streams (Musolff et al., 2017), and determines the presence of competing pelagic and benthic algae communities along river networks (Yang et al., 2021a).

We identified several approaches that attempt to capture spatial distribution within catchments either by considering surface flow distance to the outlet or nearest stream (i.e., drainage point) or by considering river network organization (e.g., stream orders). Below we highlight several potential methods that are available (but rarely implemented) for spatially-differentiated catchment characterization.

Proximity to the outlet is often used as a proxy of the length of the flow path through the subsurface and river network (Viglione et al., 2010) and can be useful to account for the attenuation effects of river networks on hydrological responses of the catchments. Skewness index is one of the metrics that quantifies spatial distribution of elements within catchments computed as a ratio of the mean flow length from the element of interest within the catchment weighted by the mean flow path length of the whole catchment (Mineau et al., 2015, Figure 10). In the case of nutrient sources (such as anthropogenic land use) their distance to the outlet is measured as distance of each elementary reach to the outlet (Ye et al., 2020) and essentially provides information about the primary location of the element of interest relative to the catchment outlet (i.e., proximal to the outlet, centered around catchment centroid or concentrated in the headwaters, Figure 10). The above-mentioned example shows that despite the identical fraction of anthropogenic land use (the most popular aggregation technique for the land use characteristics, Figure S2b), nutrient removal and export might vary considerably due to contrasting spatial distribution of the potential sources. Similarly to land use characteristics, weighting by distance to outlet can be applied to any numerical or categorical variable to allow for spatially-differentiated catchment characterization.

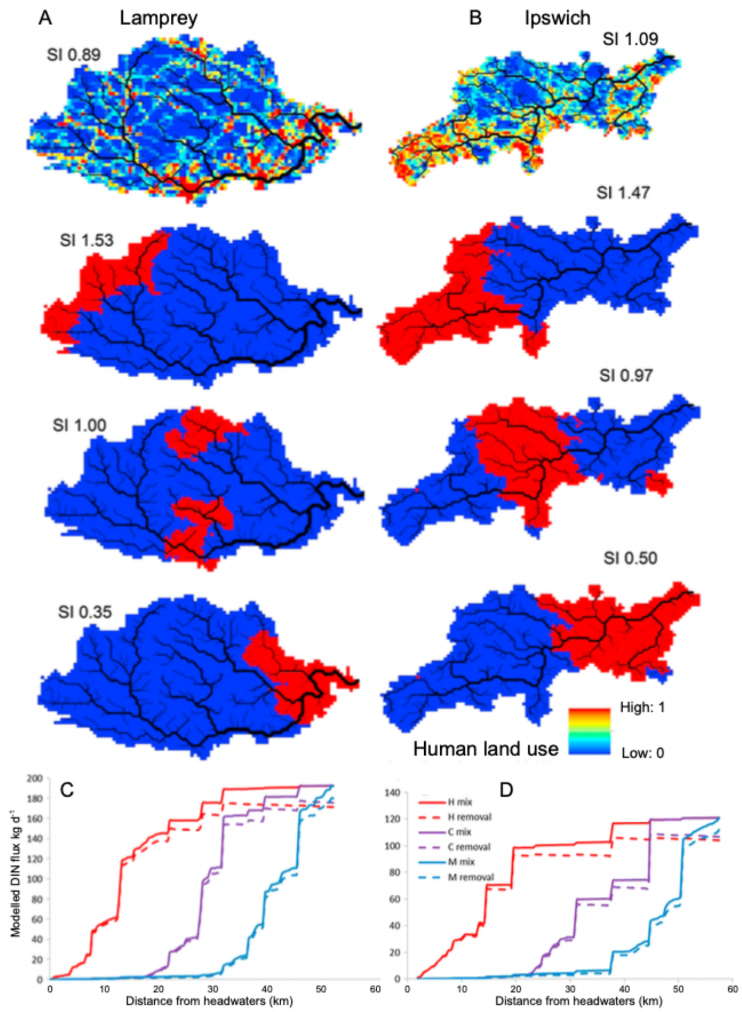

Figure 10 The effect of spatial distribution of human land use (developed and agricultural land) for nitrate export and removal: actual spatial distribution (top panel) and three scenarios corresponding to different skewness index (SI) for the Lamprey catchment (A) and for the Ipswitch catchment (B). The bottom panel shows the modeled dissolved inorganic nitrogen (DIN) for the three scenarios: human land use primarily located in the headwaters (H, SI>1), centered in the middle of the catchment (C, 1>SI>0.5), or located mostly close to the mouth (M, SI<0.5). Solid line corresponds to the conservative mixing of DIN (mix), dashed line corresponds to the simulation with the instream processes (removal). From Mineau et al. (2015), CC-BY.

The **proximity to the nearest stream** is often regarded as a proxy of travel times and might be also related to the efficiency of natural attenuation processes (Ebeling et al., 2021; Saavedra et al., 2022), but also can serve as a measure of exposure to fluvial hazards (Ceola et al., 2014). In fact, the measure of proximity to the nearest stream expressed as height above the nearest drainage (HAND) is frequently used for landscape classification (valley bottoms, hillslopes, Gharari et al., 2011; Nobre et al., 2011) in distributed hydrological modeling (Gao et al., 2019) and can be used as a metric for spatially-differentiated catchment characterization (Loritz et al., 2019). It can be particularly useful as storage units close to the stream (e.g., riparian zones and valley alluvial aquifers), despite their small total area, are hotspots of biogeochemical activity that can considerably affect nutrient concentrations in the streams (Lutz et al. 2020), and are important for streamflow generation (Glaser et al., 2018), particularly during dry periods (Käser and Hunkler, 2016).

Finally, not only distance to the outlet or the nearest stream but the **river network organization** itself in terms of its geometric and topological structure might play an important role for shaping hydrological and hydrochemical processes (Rodríguez-Iturbe and Rinaldo, 2001; Helton et al., 2018, Basso et al., 2023) and might provide important auxiliary information to facilitate spatially-differentiated aggregation of catchment descriptors. The topological structure of the river network can be quantified using **stream ordering** and **empirical scaling laws** (Horton, 1945; Schumm, 1956; Strahler, 1957). Stream ordering and scaling laws can be useful to identify the archetypes of organization of various properties that tend to evolve along the river networks (Figure 11), such as riparian vegetation (Dunn et al., 2011), human settlements (Fang et al., 2018), land use patterns (Kang et al., 2008; Miyamoto et al., 2011) or nutrient pollution sources (Yang et al., 2021b). The **width function** (Rinaldo et al., 1991; Marani et al., 1994) that represents the distribution of distances to outlet within catchments (Figure 11), is another metric to capture the topological structure of river networks and to infer the characteristic hydrological response of differently shaped networks (Moussa, 2008). Moreover, the similarity/dissimilarity between the width functions of river networks and anthropogenic landscape features such as human settlements or the capacity of wastewater treatment plants might be an insightful tool for the human impact assessment and identification of vulnerable locations (Fang et al., 2018; Yang et al., 2019).

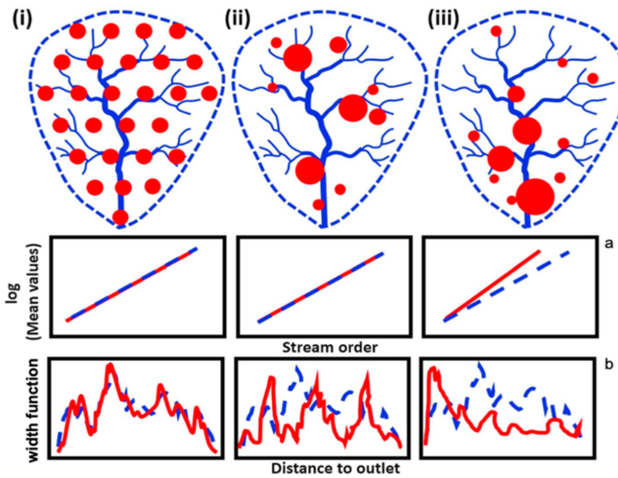

Figure 11 Three possible archetypes of human settlements organization within catchments with regard to river network: i) homogeneous spatial distribution; ii) unstructured clustering along river networks; iii) downstream clustering and corresponding representation as a) Horton's laws based on steam order and as b) width function based on distance to outlet. Blue line represents the river network and the red line represents human settlements. From Fang et al. (2018), CC-BY.

4.4 Missing ingredients for evaluation and uncertainty analysis in catchment characterization

4.4.1 Uncertainty of the original geospatial datasets

Since catchment descriptors are derived from geospatial datasets and time series, they inherit the uncertainties of their source datasets that can be associated with the measurement or sensor errors or with insufficient resolution for deriving the descriptor of interest (e.g., using coarse digital elevation model to derive density of the stream network). Although such uncertainties are difficult to quantify, there is sufficient evidence, particularly from differences between various digital elevation models (Hawker et al., 2018, derived catchment areas (Addor et al., 2017) and datasets of hydrometeorological variables (Peña-Guerrero et al., 2022), that they might be considerable.

For example, global precipitation products have considerable discrepancies due to **differences in their measurement/generation method** (satellite, reanalysis or hybrid; Beck et al., 2019). National and regional gauged or radar-based products, despite being deemed more accurate than remotely sensed or reanalysis datasets, are associated with large measurement uncertainties due to wind-induced undercatch in gauge measurements (Adam and Lettenmaier, 2003; Rasmussen et al., 2012), underestimation of rainfall amounts by radar (Haberlandt, 2007; Rabiei and Haberlandt, 2015) and interpolation uncertainty (Berndt and Haberlandt, 2018). These uncertainties will be inevitably translated to the aggregated catchment descriptors (e.g., mean annual precipitation or evaporation, Figure 12) that in turn may strongly affect the conclusions of the studies on water balance signatures that aim to identify, for instance, inter-catchment groundwater flow (Gordon et al., 2022).

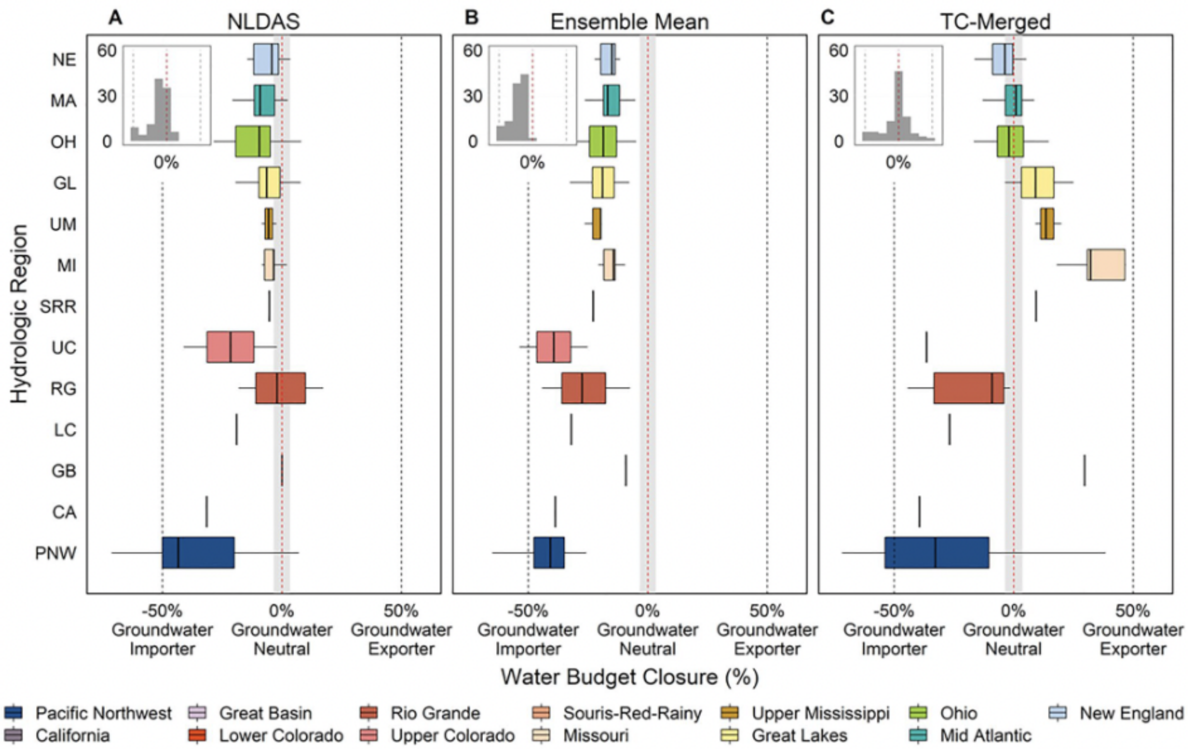

Figure 12 Difference in the classification of catchments as groundwater importer/exporter across different regions in the USA using hydrometeorological information (i.e., mean annual precipitation and mean annual evaporation) from different data sources (i.e., NLDAS, Ensemble mean (NLDAS, PRISM and Daymet for precipitation and MOD-16, NCA-LDAS and SSEBop for evaporation) and Triple Collocation (TC-Merged)). From Gordon et al 2022, CC-BY.

The **resolution of the original data sources** might contribute to the uncertainty of the aggregated catchment descriptors as well. This is particularly evident in the example of digital elevation models. Increasing spatial resolution of digital elevation model improves the accuracy of delineated stream networks (Yang et al., 2014) and correspondingly has an ultimate importance for accurate delineation of the catchment topographic and geomorphologic properties (Zhang and Montgomery, 1994; Wolock and Price, 1994). Despite recent advances, high resolution LiDAR data for producing digital elevation models is still only available for 0.005% of Earth's land surface (Hawker et al., 2018) suggesting that the uncertainties of catchment descriptors related to the resolution of the original products remain high. It is therefore advisable to investigate which characteristics and which environments are less sensitive to differences in the resolution of the original datasets (Chavan and Shrinivas, 2015), or explicitly account for scale dependence of catchment descriptors.

Descriptors aggregated from the **derived datasets** (e.g., soil hydraulic properties) might be affected by the corresponding propagating uncertainties. This is particularly the case for subsurface properties. With the emergence of digital soil mapping the historical polygon-based soil type maps were transformed into derived gridded datasets of soil properties (e.g., silt or sand content, available water capacity; Minasny and McBratney, 2016) by means of predictive models based on different environmental variables (or base maps, such as topographic and vegetation maps; McBartney et al., 2003). Due to variable accuracy of these models in space the final products of subsurface properties are associated with the **spatially variable uncertainties** (Miller and Schaetzl, 2014; Stumpf et al., 2017).

These inherent uncertainties and spatial differences in the quality of the geospatial products might result in variable relevance for inferring hydrological processes in different regions. For example, the HOST soil dataset developed by Boorman et al. (1995) for UK that classifies the soils based on the dominant flow pathways has proven to be indispensable for hydrological regionalization in the UK (e.g., UK Flood Estimation Handbook; Capell et al., 2012; McIntyre et al., 2005). However, the application of a similar procedure for hydrological classification of European soils (Schneider et al., 2007) resulted in inferior results for baseflow prediction in France (Oudin et al., 2010), indicating potentially **limited transferability of the derivation methods** across different regions, especially for subsurface properties. This is a relevant issue for the advancement of large-sample hydrology and for the development of consistent global datasets of catchment descriptors such as BasinATLAS (Linke te al., 2019) and CARAVAN (Kratzert et al., 2023). Despite undoubtful usefulness of these large consistent datasets, a considerable amount of relevant regional information might not be carried forward if it is not easily quantifiable (Gnann et al., 2021; Floriancic et al., 2022).

It is also important to note the **interplay between scale and uncertainty** might be a relevant issue for obtaining reliable catchment descriptors (Seyfried and Wilcox, 1995). At larger scales small scale variability and effects might be subsumed by emerging uncertainties resulting in disparate reports on the usefulness of certain characteristics for understanding catchment response (Wilcox et al., 2006). Therefore, it is important to identify scales appropriate for the different catchment descriptors and the complexity of their aggregation.

4.4.2 Arbitrary selection of catchment descriptors

Our review showed that in most cases the usefulness of the catchment descriptors for the investigated problem is evaluated using bivariate correlations, while out of sample cross-validation is rare. Ssegane et al. (2012b) showed that using different statistical and machine learning-based techniques for **variable selection** might result in different subsets of descriptors that are deemed essential for hydrological catchment characterization, while the effectiveness of these subsamples for regionalization tasks might vary considerably in the cross-validation (DiPrinzio et al., 2011; Tarasova et al., 2018).

We identify two broad strategies that are present in the studies we analyzed: 1) selecting an exhaustive list of descriptors and applying quantitative feature selection using statistical methods or 2) selecting few descriptors that are deemed as possible drivers based on previous experience or literature (that is however often not stated explicitly). Both approaches have shortcomings. In the first case, one has to tackle the problem of high correlation between catchment descriptors that might be related to co-evolution of climate and landscape descriptors (Merz et al., 2020a; Ebeling et al., 2021). In the second case, one risks a priori excluding key driver(s). Both approaches might be affected by spurious (i.e., non-causal) correlations, leading to erroneous conclusions and limited transferability of the results. A potential solution might be in using **perceptual models** (Beven and Chappell, 2021; McMillan et al., 2023) to facilitate **hypothesis-based selection** of catchment descriptors that should be further tested **quantitatively using cross-validation approaches** in combination with **several variable selection approaches** to mitigate potential multicollinearity effects. Using perceptual models makes the choice of descriptor selection explicit and it can help to identify main sources of epistemic uncertainty, i.e., current knowledge gaps (Wagener et al., 2021).This in turn helps to navigate our efforts on obtaining new information or explore alternative data sources for characterizing particularly uncertain catchment compartments (e.g., including expert geologist knowledge about the subsurface storage, Rogger et al., 2012; using data on sinkholes to infer the degree of secondary permeability, Gnann et al., 2021)

5. Summary and outlook

Our systematic review has identified current practices and shed light on existing biases in catchment characterization. We show that catchment characterization studies are disproportionately focused on wet and temperate environments. The descriptors derived from data sources of the land surface (i.e., digital elevation models; land use maps and hydrometeorological datasets) are used much more frequently for catchment characterization than subsurface properties regardless of research field or type of study. Temporal variability of such descriptors is often considered, while spatial and vertical variability are usually ignored when lumped aggregation methods (i.e., spatial or vertical averages) are used. The usefulness of catchment descriptors is often evaluated in terms of their explanatory power, while the uncertainty of the descriptors (originating either from the original datasets or from aggregation methods) is almost never considered. Previous studies postulated a **lack of hydrologically-informative catchment descriptors** (Oudin et al., 2010; Merz et al., 2020a) implying that physio-geographical similarity as captured by traditional descriptors does not always reflect hydrological similarity (i.e., how catchments partition, store and release water and waterborne constituents). This lack of information content might be related to the biases in our current practices that we identified: lack of appropriate descriptors for **dry environments** and the **subsurface** in general, **negligence of differentiated aggregation** techniques of catchment descriptors and the **inherent uncertainties** associated with the original datasets.

Therefore, future research on catchment characterization should more intensively focus on **dry environments** where the evidence from small scale studies suggests considerable differences in runoff generation processes compared to wetter environments. Thus suggesting a need for a different set of catchment descriptors to characterize them. It is not advisable to only focus on descriptors that are currently considered in the existing large sample datasets, since they tend to be biased towards reflecting the hydrology of wetter environments. Vegetation patterns, surface cover, the presence of soil crusts, the age of desert pavement as well as streambed texture and spatial variability of rainfall are aspects that should be considered when deriving datasets for large sample hydrology studies in dry environments.

More efforts should be invested in creating high quality regional datasets of **subsurface properties** for catchment characterization. Particularly, including information on the geomorphic setting, presence of unconsolidated material, the thickness of regolith and weathered bedrock might be crucial for comprehensive catchment characterization and identification of hydrological similarity. Moreover, more innovative indirect methods for inferring information about secondary permeability, such as number of sinkholes or karst springs (Gnann et al., 2021) might be very useful. Further development and correction of existing pedo-transfer functions by considering vegetation effects and soil structure (Or, 2020) might be another important advance to provide more reliable information about soil hydraulic properties at larger scales. New global collections of existing groundwater system conceptualizations likely provide additional information not yet widely available (Zipper et al., 2023).

While including information on **vertical organization**, particularly about subsurface layering might be hampered by data availability, considering the **spatial organization** of features within catchments can be advanced by developing novel methods that consider these aspects. We showed several examples on how distance to outlet or nearest drainage, as well as considering river network organization might be a first step in this direction.

Moreover, exploring different strategies, such as **composite catchment descriptors** as suggested by Floriancic et al. (2022) or deriving **functional catchment descriptors** (Janssen and Ameli, 2021) to obtain more comprehensive and hydrologically relevant catchment characterization might be another potential avenue. Generally, a more **hypothesis-oriented selection of catchment descriptors** backed up by perceptual models (McMillan et al., 2023) together with careful consideration of the potential **uncertainty in the original data sources** (Addor al., 2020) is advisable to limit the subjectivity of descriptor choice and uncertainty. Testing various **variable selection methods** (Ssegane et al., 2012b) and more robust evaluation of descriptor usefulness, especially in large-sample studies where **cross-**

validation is possible, might be another way to ensure the optimal choice of descriptors and their predictive potential for information transfer between catchments.

Finally, it is worth to note that **the lack of unified terminology** for catchment descriptors representing the same physical characteristic or the lack of detailed definition of implemented descriptors is seriously affecting knowledge accumulation. For example, on the one hand we have encountered several terms, such as "shape factor", "form factor", "elongation ratio" all relating to exactly the same feature, but on the other hand we have also encountered three different definitions all termed as "shape factor", while half of the studies that use this term do not provide any definition at all (see Table S2). This ambiguity limits the synthesis of the results from different studies (McMillan, 2022). As suggested by Wagener et al. (2021) and Stein et al (2022), providing a clear description and aggregation method for catchment descriptors preferably in a tabular form together with the metadata about the study catchments might help to consolidate valuable information available from local and regional studies that is currently lacking at the global scale. This might be especially important for subsurface catchment characterization where the resolution and accuracy of the global data sources does not allow us to capture the vast subsurface heterogeneity and complex vertical structure of the critical zone.

Data availability

The metadata of all extracted articles including the flags according to the PRISMA selection criteria for the analysis are provided in the Supporting Information Table S1. The detailed metadata including attribution to the research field, number of analyzed catchments and characteristics and the correspondingly indexed list of all catchment characteristics organized by main data sources are provided in the Supporting Information Table S2.

Acknowledgements

We are thankful to Columbia University Libraries for providing access to the scientific articles analyzed in this review. We thank Robin Scharsich for the help in pre-screening the scientific articles used in the analysis. LT acknowledges the financial support of the German Research Foundation (Deutsche Forschungsgemeinschaft - DFG) in terms of the Research Unit "Space-time dynamics of extreme floods" FOR2416 and of the Helmholtz Centre for Environmental Research – UFZ. Support for SG and TW was provided by the Alexander von Humboldt Foundation in the framework of the Alexander von Humboldt Professorship endowed by the German Federal Ministry of Education and Research.

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