

# Caravan - A global community dataset for large-sample hydrology

Frederik Kratzert<sup>1,\*</sup>, Grey Nearing<sup>2</sup>, Nans Addor<sup>3,4</sup>, Tyler Erickson<sup>5</sup>, Martin Gauch<sup>6</sup>, Oren Gilon<sup>7</sup>, Lukas Gudmundsson<sup>8</sup>, Avinatan Hassidim<sup>7</sup>, Daniel Klotz<sup>6</sup>, Sella Nevo<sup>7</sup>, Guy Shalev<sup>7</sup>, and Yossi Matias<sup>7</sup>

<sup>1</sup>Google Research, Vienna, Austria

<sup>2</sup>Google Research, Mountain View, CA, United States

<sup>3</sup>Geography, College of Life and Environmental Sciences, University of Exeter, Exeter, UK

<sup>4</sup>Fathom, Square Works, Bristol, UK

<sup>5</sup>Google, Mountain View, CA, USA

<sup>6</sup>Institute for Machine Learning, Johannes Kepler University, Linz, Austria

<sup>7</sup>Google Research, Tel Aviv, Israel

<sup>8</sup>Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland

\*corresponding author: Frederik Kratzert (kratzert@google.com)

**THIS IS AN UNREVIEWED PREPRINT**

## ABSTRACT

High-quality datasets are essential to support hydrological science and modeling. Several CAMELS (Catchment Attributes and Meteorology for Large-sample Studies) datasets exist for specific countries or regions, however these datasets lack standardization, which makes global studies difficult. This paper introduces a dataset called *Caravan* (a series of CAMELS) that standardizes and aggregates seven existing large-sample hydrology datasets. *Caravan* includes meteorological forcing data, streamflow data, and static catchment attributes (e.g., geophysical, sociological, climatological) for 2532 catchments. Most importantly, *Caravan* is both a dataset and open-source software that allows members of the hydrology community to extend the dataset to new locations by extracting forcing data and catchment attributes in the cloud. Our vision is for *Caravan* to democratize the creation and use of globally-standardized large-sample hydrology datasets. *Caravan* is a truly global open-source community resource.

## Background & Summary

Data underpin our understanding of the storage and transport of water at the Earth's surface. Hydrological processes (e.g., streamflow generation) are governed by hydroclimatic variables (e.g., rainfall, temperature, humidity) and landscape characteristics (e.g., soils, landcover, human intervention). These interactions govern the availability of water resources and the occurrence of extreme events like floods and droughts.

Detailed datasets combining hydroclimatic time series, landscape attributes, and/or hydrological response variables like streamflow exist for many experimental catchments, in many cases spanning decades<sup>1-3</sup>. However, it is not possible to capture the diversity of hydrological behavior from any individual watershed. In parallel, there also exist tens of thousands of gauges monitoring rivers across the world. Although data available from these gauges are limited in that they do not describe all of the hydrological processes in a given watershed, the large number of gauges means that they cover a wide range of hydrological regimes and extreme events<sup>4-7</sup>. Gupta et al.<sup>8</sup> argued that large sample sizes allow for assessment of the generality of hydrological models and research findings. Large sample sizes also allow for large-scale research like detecting and attributing systematic shifts in terrestrial water availability at regional<sup>9,10</sup> to global scales<sup>11,12</sup>. Moreover, large sample datasets are necessary for developing generalizable data-driven models<sup>13-16</sup>.

Recognizing this has led to the development of a sub-discipline in the hydrological sciences called *large-sample hydrology* (LSH), which relies on data from hundreds to thousands of catchments<sup>17</sup>. There are an increasing number of publicly available LSH datasets. Arguably, the first open LSH dataset was from the Model Parameter Estimation Experiment (MOPEX)<sup>18</sup>, which contains data from 431 basins within the United States through 2003. Later datasets were developed for specific countries or regions, including Australia<sup>19</sup>, Austria<sup>20</sup>, Brazil<sup>21</sup>, North-America<sup>22</sup>, China<sup>23</sup>, Chile<sup>24</sup>, Europe<sup>25</sup>, Great Britain<sup>26</sup>, Thailand<sup>27</sup>, the United States<sup>28,29</sup>, and the Arctic<sup>30</sup>. Many of these are referred to as *Catchment Attributes and MEteorology for*

38 *Large-sample Studies (CAMELS)* datasets<sup>19,21,24,26,29</sup>.

39 Although none of the existing CAMELS datasets are global, there are global collections of streamflow data like the Global  
40 Streamflow Indices and Metadata Archive (GSIM)<sup>31,32</sup>, which provides monthly and seasonal streamflow indices for 35,000+  
41 locations, and the Global Runoff Data Base<sup>33</sup>, which provides river discharge estimates at 10,000+ locations. Both of these  
42 collections, however, are not coupled with catchment attributes or meteorological forcing data. Critically, GSIM does not  
43 provide daily streamflow data (only indices), and GRDC does not allow for redistribution of raw data, which makes it difficult to  
44 standardize with other datasets. Furthermore, although data from 10,000+ stations are available through GRDC, both the quality  
45 of the available records and the period of record for individual basins varies significantly<sup>32</sup>. On the other hand, HydroATLAS<sup>34</sup>  
46 provides global catchment attributes, but does not include meteorological or streamflow data. There are also proprietary or  
47 non-public hydrological datasets that have been used for hydrological research – for example, datasets used by Beck et al.,<sup>35,36</sup>  
48 for global model calibration or by Blöschl et al.<sup>37</sup> for extrapolating climate change impacts on flooding (less than a third of one  
49 percent of the daily time series used in the latter study are publicly available, last access 20th March 2022). Proprietary datasets  
50 are a roadblock to open, collaborative, reproducible, and extensible research.

51 Aside from the fact that no comprehensive, global LSH dataset exists, Addor et al.<sup>17</sup> identified four major limitations  
52 of many of the existing region-specific datasets: (i) lack of common standards to allow for intercomparison, (ii) lack of  
53 metadata and uncertainty estimates to assess data reliability, (iii) lack of information about human interventions, and (iv)  
54 limited accessibility. Addor et al.<sup>17</sup> also outlined desiderata for standardizing and automating the development of LSH datasets,  
55 including (i) basic data requirements, (ii) naming conventions for hydrologically-relevant variables, (iii) publicly available  
56 data processing code, (iv) uncertainty estimates, (v) anthropogenic descriptors, and (vi) adhering to FAIR data standards<sup>38</sup>.  
57 They propose that community, cloud-based infrastructure could help overcome these limitations, by allowing for the use and  
58 development of standardized practices and codebases.

59 The *Caravan* dataset presented here is a step toward realizing this vision. The basis for Caravan is a collection of  
60 region-specific datasets, which are merged and standardized in a way that is designed with the following characteristics:

- 61 1. Standardized: Data are standardized globally meaning that the same meteorological and landscape variables exist for all  
62 catchments, and are derived using the same procedures from the same source datasets.
- 63 2. Open: All data are publicly available with an open license.
- 64 3. Extensible: All software tools and source datasets used to produce Caravan are open and accessible through a cloud  
65 platform (Google Earth Engine) to enable others to extend (i.e., add catchments to) the dataset.

66 The third point is especially important. Most streamflow gauges are maintained by local or national organizations, and the data  
67 from these gauges are rarely FAIR (Findable, Accessible, Interoperable and Re-usable). Caravan is designed to be extensible,  
68 so that anyone can easily derive meteorological forcings and landscape attributes for additional catchments using a standardized  
69 procedure. This allows new catchments to be used in the context of this larger dataset (e.g., for training models, assessing  
70 relative climate impacts, etc.), and it allows organizations with streamflow data from any number of catchments (from one to  
71 thousands) to quickly and easily add their data to the larger public Caravan dataset in a way that is standardized with all other  
72 catchment data. Our vision is for Caravan to be the platform for a larger community data resource – we see this as perhaps  
73 the most direct path to developing a truly open global hydrological dataset. The current Caravan dataset that we introduce  
74 here includes streamflow observations from 2532 basins, spanning most Global Environmental Stratification (GENS) climate  
75 zones<sup>39</sup>, with the exception of arctic, extreme cold, and arid zones (Figure 1). Caravan includes daily data from almost four  
76 decades (1981-2020), including catchments that experienced significant climate trends (Figure 2).

## 77 **Methods**

### 78 **Basin Selection & Streamflow Data**

79 Daily streamflow observations for the 2532 basins currently in Caravan were aggregated from several existing open datasets:

- 80 • 482 basins from CAMELS (US)<sup>28</sup>
- 81 • 150 basins from CAMELS-AUS<sup>19</sup>
- 82 • 376 basins from CAMELS-BR<sup>21</sup>
- 83 • 314 basins from CAMELS-CL (using an updated Version from January 2022)<sup>24</sup>
- 84 • 408 basins from CAMELS-GB<sup>26</sup>
- 85 • 323 basins from HYPES<sup>22</sup>
- 86 • 479 basins from LamaH-CE<sup>20</sup>

87 These datasets were selected because (i) they include catchment boundaries for each streamflow gauge, and (ii) because their  
88 licenses allow redistribution. We only include basins equal or larger than 100 km<sup>2</sup> and smaller than 2000km<sup>2</sup>, and streamflow  
89 data is normalized by catchment area to units of *mm/day*. All data are reported in the local time zone (non-daylight saving time  
90 for the entire year) of the gauge station, which is included in metadata.

91 Time periods of available streamflow observations varies between basins, however we did not include any streamflow data  
92 prior to 1981 because this is the beginning of the ERA5-Land reanalysis, which was used to derive meteorological forcing data.  
93 Figure 3 shows density of streamflow records through time (left) and the distribution of lengths of daily streamflow records  
94 (right), emphasizing that comparatively long flow time series are available for the Caravan catchments (the median length is 34  
95 years).

## 96 Meteorological Forcing Data

97 Caravan includes meteorological forcing data from ERA5-Land<sup>40</sup>. This choice was made for the following reasons:

- 98 • Global coverage: Although ERA5-Land data products are often lower-accuracy (i.e., more uncertain) than local, high-  
99 resolution meteorological data sets, only globally available data sets allow for comparative studies at a global scale.
- 100 • Sub-daily (e.g., hourly) resolution: All daily average streamflow observations in the source datasets are reported in the  
101 corresponding local time of the gauge station. In contrast, global meteorological data products are usually provided in  
102 GMT+0. To be able to calculate the matching daily average meteorological forcing data for the daily averaged streamflow  
103 observation, it is therefore necessary to have sub-daily meteorological data, so that we can shift the meteorological data  
104 according to the local time zone of the gauge station, before computing daily aggregates.
- 105 • Availability in the cloud: one of our goals was to do all heavy computing tasks in the cloud (here: Google Earth Engine).  
106 ERA5-Land provides hourly data on Google Earth Engine.
- 107 • Permissive license: A core principle of Caravan is to democratize LSH datasets and dataset development. ERA5-Land  
108 has a permissive license that allows free distribution.

109 ERA5-Land meteorological variables used in Caravan are listed in Table 1 – these are typical variables used as forcing  
110 data (or boundary conditions) for hydrology and land surface models. We first computed the area-weighted spatial average  
111 for each variable in each catchment area from hourly spatial data (~9km spatial resolution) and shifted the hourly time series  
112 (natively at GMT+0) to the local time of each gauge. We then computed different daily statistics for each variable according to  
113 the Aggregation column in Table 1.

## 114 Reference Model States

115 In addition to meteorological forcing data, Caravan includes time series of modeled soil moisture and snow states from  
116 ERA5-Land (Table 2). These time series are included to provide reference values or benchmark values for studies that analyze  
117 or model hydrological states. These time series data were processed in the same way as meteorological forcing data.

## 118 Catchment Attributes

119 Caravan includes two sets of catchment attributes: (i) attributes derived from HydroATLAS<sup>34,41</sup> and (ii) climate attributes  
120 derived from the daily ERA5-Land time series included in Caravan. The latter are similar to the climate attributes provided in  
121 CAMELS-US<sup>29</sup>. The reasons for choosing HydroATLAS as the source for the former are similar to the reasons for choosing  
122 ERA5-Land for time series data: HydroATLAS has global coverage with a license that allows for redistribution.

123 The catchment attributes derived from HydroATLAS use the highest resolution shape file available in that dataset (level  
124 12). The level 12 HydroATLAS polygons are, for the vast majority of basins, smaller than the catchment boundaries for each  
125 gauge station provided by the respective CAMELS datasets – i.e., a single polygon representing the drainage area for a specific  
126 gauge include multiple HydroATLAS polygons. Therefore, we first computed the spatial join of the HydroATLAS polygons  
127 and the catchment boundaries and then derived the catchment attributes as an area-weighted aggregate (see the Aggregation  
128 column in Table 3). Catchment attributes included in Caravan can be loosely grouped into the following categories: hydrology,  
129 physiography, climatology, soils & geology, land cover characteristics, and anthropogenic influences. A full list of all catchment  
130 attributes derived from HydroATLAS is given in Table 3 and a list of attributes derived from ERA5-Land time series is given in  
131 Table 4. Caravan attributes additionally include the latitude and longitude coordinates of each gauge station, copied directly  
132 from the source datasets, as well as the catchment drainage area derived directly from CAMELS shapefiles.

## 133 Data Processing in the Cloud

134 The major computational challenge for developing LSH datasets is processing gridded meteorological and attributes data. To  
135 make the development and augmentation of Caravan as democratic as possible (i.e., to make it as easy as possible for anyone to  
136 add new watersheds or new data layers to the dataset), all of our data processing scripts use Google Earth Engine. Google  
137 Earth Engine<sup>42</sup> is a free-to-use cloud service with a large catalogue of geospatial data, including all of the datasets described  
138 above. This has two benefits: it is not necessary for users to download and store large amounts of gridded meteorological  
139 data, and does not require any specific hardware. Any individual hydrologist, modeler, researcher, or student should be able to  
140 process even large numbers of new watersheds with minimal effort or expense. All that is necessary to add a new gauge to the  
141 Caravan dataset is a shapefile representing the drainage area of the catchment, plus a timeseries of daily or subdaily streamflow  
142 (discharge) values from that gauge in local time. Instructions about how to add new catchments to Caravan are provided in a  
143 Readme file in the dataset repository.

## 144 Data Records

145 The current version of the Caravan dataset (2532 watersheds) is available at [https://doi.org/10.5281/zenodo.  
146 6647189](https://doi.org/10.5281/zenodo.6647189). A project homepage is available at <https://github.com/kratzert/Caravan/>, including all code and  
147 where news and updates are announced.

148 The dataset is organized into the following subfolders:

- 149 • The *attributes* folder contains one subfolder per source dataset, which each contain two csv (comma separated values)  
150 files. One file ('attributes\_hydroatlas\_{source}.csv') contains attributes derived from HydroATLAS and the other file  
151 ('attributes\_caravan\_{source}.csv') contains limate indices derived from ERA5-Land, where {source} indicates the  
152 corresponding source data set (e.g. *camelsgb* for CAMELS-GB, *camelscl* for CAMELS-CL, and so on). The first column  
153 in all attributes file is called 'gauge\_id' and contains a unique basin identifier of the form '{source}\_{id}', where {source}  
154 again is the abbreviation of the corresponding source dataset, and {id} is the basin id as defined in the original source  
155 dataset.
- 156 • The *shapefiles* folder contains one subfolder per source dataset. Each of these subfolders contains a shapefile with the  
157 catchment boundaries of each basin within that dataset. These are the shapefiles that were used to derive the catchment  
158 attributes and ERA5-Land time series data. Each polygon in a given shapefile has a field 'gauge\_id' that contains the  
159 unique basin identifier.
- 160 • The *timeseries* folder contains two subfolders, *csv* and *netcdf*, that both share the same structure and contain the same  
161 data, once as csv-files and once as netCDF files. Each of these two subfolders contains one subfolder per source dataset.  
162 Within these source dataset specific subdirectories, there is one file (either csv or netCDF) per basin, containing all  
163 time series data (meteorological forcings, state variables, and streamflow). The netCDF files also contain metadata  
164 information, including physical units, timezones, and information on the data sources.
- 165 • The *code* folder contains all scripts and Jupyter notebooks that were used to derive the data set. These scripts can be used  
166 to extend the data set to any new basin in the world. Instructions are included in the README.md file contained in this  
167 folder.
- 168 • The *licenses* folder contains license information of all data included in Caravan and for Caravan itself. General license  
169 information are listed in the README.md file in this directory, source dataset specific information are listed in the files  
170 located in the source dataset specific subdirectories.
- 171 • The *README.md* file in the main directory includes a description of the dataset structure, information on the units of  
172 time series data, and time zones.

173 All time series data except streamflow are aggregated (daily and spatially over basins) from ERA5-Land. ERA5-Land is  
174 available directly from<sup>43</sup>, however we used the Google Earth Engine repository. HydroATLAS attributes were derived from  
175 the HydroATLAS dataset<sup>44</sup>. Streamflow time series are collected from the respective region-specific repositories: Australia<sup>45</sup>,  
176 Brazil<sup>46</sup>, Canada<sup>22</sup>, Chile<sup>47</sup>, Great Britain<sup>48</sup>, LamaH-CE (Austrian territory and Danube catchment up to Bratislava)<sup>49</sup>, and the  
177 United States:<sup>50</sup>.

## 178 Technical Validation

### 179 Aggregating HydroATLAS attributes

180 The majority of catchment attributes are derived from HydroATLAS. The key challenge in extracting data from HydroAtlas is  
181 to define which HydroATLAS polygons are within a given gauge's drainage area. The primary complication is that all datasets

182 — i.e., the various CAMELS datasets and HydroATLAS use shapefiles derived from different digital elevation maps (DEM) at  
183 different spatial resolution. This means that catchment boundaries from the source datasets do not perfectly align with the  
184 polygons in HydroATLAS. An example of this is shown in Figure 4. This figure shows the drainage area for a particular gauge,  
185 as specified by the shapefile in the CAMELS dataset (first subpanel), the collocated HydroATLAS subbasin polygons (second  
186 panel), and the mismatch between the two due to different datasets deriving catchment boundaries from different DEMs (third  
187 panel).

188 Because of this mismatch along catchment boundaries between different watershed delineations in different datasets, we  
189 chose to only include gauges with total drainage areas of at least  $100\text{km}^2$ . In smaller catchments, this boundary effect can  
190 represent a significant fraction of the total area of the catchment – an example of this is illustrated in Figure 5.

## 191 **Validating meteorological time series**

192 Like most data about the natural environment, hydrological data is typically associated with significant uncertainty. Quantifying  
193 uncertainty is a central part of hydrological research<sup>51,52</sup>, and usually involves intensive field campaigns<sup>53,54</sup>, statistical  
194 comparison between several data products<sup>55–57</sup>, or modeling studies<sup>58,59</sup> — all of which are outside the scope of the current  
195 project. We can, however, statistically verify the processing tools that were used to develop the Caravan data from existing  
196 datasets. We did this verification by comparing Caravan-derived meteorological forcings (from ERA5–Land) with forcings  
197 from CAMELS-US. CAMELS-US was chosen because it includes three independent meteorological data sources (NLDAS,  
198 Maurer, DayMet), which allows us to contextualize the variability between CAMELS-US forcings and Caravan forcings. There  
199 will always be some amount of variability between any two meteorological datasets, and having three meteorological data  
200 products allows us to contextualize any variability between Caravan features and CAMELS-US features.

201 We calculated the correlation (Pearson  $r$ ) between each pair of forcing data products (NLDAS, Maurer, DayMet, ERA5–  
202 Land) separately in each basin ( $n=482$ ) for three meteorological variables: total daily precipitation and daily maximum  
203 and minimum temperatures. We then used a set of one-tailed, paired t-tests to test hypotheses that for each of the three  
204 meteorological variables, correlations between Caravan and any individual CAMELS-US data product were significantly  
205 ( $\alpha = 0.90$ ) lower than correlations between each pair of CAMELS-US forcing products. Figure 6 shows the results of these  
206 tests. Although certain forcings are more highly correlated than others (e.g., DayMet and Maurer are more highly correlated  
207 than DayMet and NLDAS), correlations between Caravan and CAMELS-US data products were not consistently lower than  
208 correlations between different CAMELS-US data products.

## 209 **Usage Notes**

210 Our vision for Caravan is as the foundation of a dynamically growing community LSH dataset that anyone in the hydrology  
211 community can access and augment. Currently, the spatial distribution of basins included in Caravan is limited to a few regions  
212 in the world, see Fig. 7. We hope that some users will be willing (and allowed) to share their data, so that Caravan, over time,  
213 will contain discharge data from most parts of the world. Detailed instructions for adding new catchments to Caravan are  
214 provided in the dataset repository, as well as in the code repository. This includes all code necessary to derive meteorological  
215 and attributes data on Google Earth Engine for any new basin globally. All computation can be done for free using Google  
216 Earth Engine.

217 In the introduction, we noted that Addor et al.<sup>17</sup> listed six desiderata for LHS datasets. Caravan meets five of those six  
218 criteria – the missing desideratum is to have uncertainty estimates on all data components. Assessing uncertainty in hydrological  
219 data is difficult without relying on strong assumptions (often, some type of hydrological model), and we expect that future work  
220 will apply various methods for quantifying the uncertainty in global rainfall-runoff datasets. Perhaps that a comparison of the  
221 attributes and timeseries provided in Carvan, and those from the LSH original datasets, could provide new insights into their  
222 uncertainty, and inform the selection of datasets for hydrology.

## 223 **Code Availability**

224 The code that was used to produce the Caravan dataset is available at <https://github.com/kratzert/Caravan/>  
225 and a static snapshot of the time of the submission was uploaded to <https://doi.org/10.5281/zenodo.6647189>.

## 226 **References**

- 227 1. Goodrich, D. *et al.* The usda-ars experimental watershed network: Evolution, lessons learned, societal benefits, and moving  
228 forward. *Water Resour. Res.* **57**, e2019WR026473 (2021).
- 229 2. Likens, G. E. The watershed-ecosystem approach. *Hydrol. Process.* **35**, e13977, <https://doi.org/10.1002/hyp.13977> (2021).  
230 <https://onlinelibrary.wiley.com/doi/pdf/10.1002/hyp.13977>.

- 231 3. Goodman, K. J., Parker, S. M., Edmonds, J. W. & Zeglin, L. H. Expanding the scale of aquatic sciences: the role of the  
232 national ecological observatory network (neon). *Freshw. Sci.* **34**, 377–385 (2015).
- 233 4. Kovács, G. Proposal to construct a coordinating matrix for comparative hydrology. *Hydrol. Sci. J.* **29**, 435–443 (1984).
- 234 5. Falkenmark, M. & Chapman, T. *Comparative hydrology: An ecological approach to land and water resources* (Unesco,  
235 1989).
- 236 6. Andreassian, V., Hall, A., Chahinian, N. & Schaake, J. Introduction and synthesis: Why should hydrologists work on a  
237 large number of basin data sets? (2006).
- 238 7. Blöschl, G. *et al.* Twenty-three unsolved problems in hydrology (uph)—a community perspective. *Hydrol. sciences journal*  
239 **64**, 1141–1158 (2019).
- 240 8. Gupta, H. V. *et al.* Large-sample hydrology: a need to balance depth with breadth. *Hydrol. Earth Syst. Sci.* **18**, 463–477  
241 (2014).
- 242 9. Stahl, K. *et al.* Streamflow trends in europe: evidence from a dataset of near-natural catchments. *Hydrol. Earth Syst. Sci.*  
243 **14**, 2367–2382, [10.5194/hess-14-2367-2010](https://doi.org/10.5194/hess-14-2367-2010) (2010).
- 244 10. Gudmundsson, L., Seneviratne, S. I. & Zhang, X. Anthropogenic climate change detected in european renewable freshwater  
245 resources. *Nat. Clim. Chang.* **7**, 813–816 (2017).
- 246 11. Gudmundsson, L., Leonard, M., Do, H. X., Westra, S. & Seneviratne, S. I. Observed trends in global indicators of mean  
247 and extreme streamflow. *Geophys. Res. Lett.* **46**, 756–766, <https://doi.org/10.1029/2018GL079725> (2019).
- 248 12. Gudmundsson, L. *et al.* Globally observed trends in mean and extreme river flow attributed to climate change. *Science*  
249 **371**, 1159–1162, [10.1126/science.aba3996](https://doi.org/10.1126/science.aba3996) (2021).
- 250 13. Kratzert, F. *et al.* Towards learning universal, regional, and local hydrological behaviors via machine learning applied to  
251 large-sample datasets. *Hydrol. Earth Syst. Sci.* **23**, 5089–5110, [10.5194/hess-23-5089-2019](https://doi.org/10.5194/hess-23-5089-2019) (2019).
- 252 14. Kratzert, F. *et al.* Toward improved predictions in ungauged basins: Exploiting the power of machine learning. *Water*  
253 *Resour. Res.* **55**, 11344–11354, <https://doi.org/10.1029/2019WR026065> (2019).
- 254 15. Ghiggi, G., Humphrey, V., Seneviratne, S. I. & Gudmundsson, L. Grun: an observation-based global gridded runoff dataset  
255 from 1902 to 2014. *Earth Syst. Sci. Data* **11**, 1655–1674, [10.5194/essd-11-1655-2019](https://doi.org/10.5194/essd-11-1655-2019) (2019).
- 256 16. Ghiggi, G., Humphrey, V., Seneviratne, S. I. & Gudmundsson, L. G-run ensemble: A multi-forcing observation-based  
257 global runoff reanalysis. *Water Resour. Res.* **57**, e2020WR028787, <https://doi.org/10.1029/2020WR028787> (2021).
- 258 17. Addor, N. *et al.* Large-sample hydrology: recent progress, guidelines for new datasets and grand challenges. *Hydrol. Sci. J.*  
259 **65**, 712–725 (2020).
- 260 18. Schaake, J., Cong, S. & Duan, Q. Us mopex data set. Tech. Rep., Lawrence Livermore National Lab.(LLNL), Livermore,  
261 CA (United States) (2006).
- 262 19. Fowler, K. J., Acharya, S. C., Addor, N., Chou, C. & Peel, M. C. CAMELS-AUS: hydrometeorological time series and  
263 landscape attributes for 222 catchments in australia. *Earth Syst. Sci. Data* **13**, 3847–3867 (2021).
- 264 20. Klingler, C., Schulz, K. & Herrnegger, M. LamaH-CE: Large-sample data for hydrology and environmental sciences for  
265 central europe. *Earth Syst. Sci. Data* **13**, 4529–4565 (2021).
- 266 21. Chagas, V. B. *et al.* CAMELS-BR: hydrometeorological time series and landscape attributes for 897 catchments in brazil.  
267 *Earth Syst. Sci. Data* **12**, 2075–2096 (2020).
- 268 22. Arsenault, R. *et al.* A comprehensive, multisource database for hydrometeorological modeling of 14,425 north american  
269 watersheds. *Sci. Data* **7**, 1–12 (2020).
- 270 23. Hao, Z. *et al.* CCAM: China catchment attributes and meteorology dataset. *Earth Syst. Sci. Data* **13**, 5591–5616 (2021).
- 271 24. Alvarez-Garreton, C. *et al.* The CAMELS-CL dataset: catchment attributes and meteorology for large sample studies—chile  
272 dataset. *Hydrol. Earth Syst. Sci.* **22**, 5817–5846 (2018).
- 273 25. Kuentz, A., Arheimer, B., Hundecha, Y. & Wagener, T. Understanding hydrologic variability across europe through  
274 catchment classification. *Hydrol. Earth Syst. Sci.* **21**, 2863–2879 (2017).
- 275 26. Coxon, G. *et al.* CAMELS-GB: Hydrometeorological time series and landscape attributes for 671 catchments in great  
276 britain. *Earth Syst. Sci. Data* **12**, 2459–2483 (2020).
- 277 27. Thailand water level and river discharge observation by royal irrigation department. [http://hydro.iis.u-tokyo.ac.jp/GAME-T/  
278 GAIN-T/routine/rid-river/index.html](http://hydro.iis.u-tokyo.ac.jp/GAME-T/GAIN-T/routine/rid-river/index.html). Accessed: 2022-03-14.

- 279 **28.** Newman, A. *et al.* Development of a large-sample watershed-scale hydrometeorological data set for the contiguous usa:  
280 data set characteristics and assessment of regional variability in hydrologic model performance. *Hydrol. Earth Syst. Sci.* **19**,  
281 209–223 (2015).
- 282 **29.** Addor, N., Newman, A. J., Mizukami, N. & Clark, M. P. The CAMELS data set: catchment attributes and meteorology for  
283 large-sample studies. *Hydrol. Earth Syst. Sci.* **21**, 5293–5313 (2017).
- 284 **30.** R-articnet – a regional, electronic, hydrographic data network for the arctic region. [https://www.r-arcticnet.sr.unh.edu/v4.0/  
285 index.html](https://www.r-arcticnet.sr.unh.edu/v4.0/index.html). Accessed: 2022-03-14.
- 286 **31.** Do, H. X., Gudmundsson, L., Leonard, M. & Westra, S. The global streamflow indices and metadata archive (gsim)–part 1:  
287 The production of a daily streamflow archive and metadata. *Earth Syst. Sci. Data* **10**, 765–785 (2018).
- 288 **32.** Gudmundsson, L., Do, H. X., Leonard, M. & Westra, S. The global streamflow indices and metadata archive (GSIM)–part  
289 2: Quality control, time-series indices and homogeneity assessment. *Earth Syst. Sci. Data* **10**, 787–804 (2018).
- 290 **33.** Grdc – global runoff data center. [https://www.bafg.de/GRDC/EN/02\\_srvcs/21\\_tmsrs/210\\_prtl/prtl\\_node.html](https://www.bafg.de/GRDC/EN/02_srvcs/21_tmsrs/210_prtl/prtl_node.html). Accessed:  
291 2022-03-14.
- 292 **34.** Linke, S. *et al.* Global hydro-environmental sub-basin and river reach characteristics at high spatial resolution. *Sci. data* **6**,  
293 1–15, <https://doi.org/10.1038/s41597-019-0300-6> (2019).
- 294 **35.** Beck, H. E. *et al.* Global-scale regionalization of hydrologic model parameters. *Water Resour. Res.* **52**, 3599–3622 (2016).
- 295 **36.** Beck, H. E. *et al.* Global fully distributed parameter regionalization based on observed streamflow from 4,229 headwater  
296 catchments. *J. Geophys. Res. Atmospheres* **125**, e2019JD031485 (2020).
- 297 **37.** Blöschl, G. *et al.* Changing climate both increases and decreases european river floods. *Nature* **573**, 108–111 (2019).
- 298 **38.** Wilkinson, M. D. *et al.* The fair guiding principles for scientific data management and stewardship. *Sci. data* **3**, 1–9 (2016).
- 299 **39.** Metzger, M. J. *et al.* A high-resolution bioclimate map of the world: a unifying framework for global biodiversity research  
300 and monitoring. *Glob. Ecol. Biogeogr.* **22**, 630–638 (2013).
- 301 **40.** Muñoz-Sabater, J. *et al.* Era5-land: A state-of-the-art global reanalysis dataset for land applications. *Earth Syst. Sci. Data*  
302 **13**, 4349–4383 (2021).
- 303 **41.** Lehner, B. Hydroatlas version 1.0 data download, <https://doi.org/10.6084/m9.figshare.9890531.v1> (2022).
- 304 **42.** Gorelick, N. *et al.* Google earth engine: Planetary-scale geospatial analysis for everyone. *Remote. Sens. Environ.*  
305 [10.1016/j.rse.2017.06.031](https://doi.org/10.1016/j.rse.2017.06.031) (2017).
- 306 **43.** Muñoz Sabater, J. *et al.* Era5-land hourly data from 1981 to present. *Copernicus Clim. Chang. Serv. (C3S) Clim. Data*  
307 *Store (CDS)* **10**, <https://doi.org/10.24381/cds.e2161bac> (2021).
- 308 **44.** Lehner, B., Linke, S. & Thieme, M. Hydroatlas version 1.0. <https://doi.org/10.6084/m9.figshare.9890531.v1> (2019).
- 309 **45.** Fowler, K., Acharya, S. C., Addor, N., Chou, C. & Peel, M. CAMELS-AUS v1: Hydrometeorological time series and  
310 landscape attributes for 222 catchments in australia, [10.1594/PANGAEA.921850](https://doi.org/10.1594/PANGAEA.921850) (2020).
- 311 **46.** Chagas, V. B. P. *et al.* CAMELS-BR: Hydrometeorological time series and landscape attributes for 897 catchments in  
312 brazil, [10.5281/zenodo.3964745](https://doi.org/10.5281/zenodo.3964745) (2020).
- 313 **47.** Alvarez-Garreton, C. *et al.* The CAMELS-CL dataset: catchment attributes and meteorology for large sample studies -  
314 chile dataset, [10.1594/PANGAEA.894885](https://doi.org/10.1594/PANGAEA.894885) (2018).
- 315 **48.** Coxon, G. *et al.* Catchment attributes and hydro-meteorological timeseries for 671 catchments across great britain  
316 (CAMELS-GB), [10.5285/8344e4f3-d2ea-44f5-8afa-86d2987543a9](https://doi.org/10.5285/8344e4f3-d2ea-44f5-8afa-86d2987543a9) (2020).
- 317 **49.** Klingler, C., Kratzert, F., Schulz, K. & Herrnegger, M. LamaH-CE: Large-sample data for hydrology and environmental  
318 sciences for central europe, [10.5281/zenodo.5153305](https://doi.org/10.5281/zenodo.5153305) (2021).
- 319 **50.** Newman, A. *et al.* A large-sample watershed-scale hydrometeorological dataset for the contiguous usa, [10.5065/  
320 D6MW2F4D](https://doi.org/10.5065/D6MW2F4D) (2014).
- 321 **51.** McMillan, H. K., Westerberg, I. K. & Krueger, T. Hydrological data uncertainty and its implications. *Wiley Interdiscip.*  
322 *Rev. Water* **5**, e1319 (2018).
- 323 **52.** Beven, K. Facets of uncertainty: epistemic uncertainty, non-stationarity, likelihood, hypothesis testing, and communication.  
324 *Hydrol. Sci. J.* **61**, 1652–1665 (2016).
- 325 **53.** Colliander, A. *et al.* Validation of smap surface soil moisture products with core validation sites. *Remote. Sens. Environ.*  
326 **191**, 215–231 (2017).

- 327 **54.** Habib, E. & Krajewski, W. F. Uncertainty analysis of the trmm ground-validation radar-rainfall products: Application to  
 328 the teflun-b field campaign. *J. applied meteorology* **41**, 558–572 (2002).
- 329 **55.** Kumar, S. V., Dirmeyer, P. A., Peters-Lidard, C. D., Bindlish, R. & Bolten, J. Information theoretic evaluation of satellite  
 330 soil moisture retrievals. *Remote. Sens. Environ.* **204**, 392–400 (2018).
- 331 **56.** Nearing, G. S. *et al.* Nonparametric triple collocation. *Water Resour. Res.* **53**, 5516–5530 (2017).
- 332 **57.** Alemohammad, S. H., McColl, K. A., Konings, A. G., Entekhabi, D. & Stoffelen, A. Characterization of precipitation  
 333 product errors across the united states using multiplicative triple collocation. *Hydrol. Earth Syst. Sci.* **19**, 3489–3503  
 334 (2015).
- 335 **58.** McMillan, H., Jackson, B., Clark, M., Kavetski, D. & Woods, R. Rainfall uncertainty in hydrological modelling: An  
 336 evaluation of multiplicative error models. *J. Hydrol.* **400**, 83–94 (2011).
- 337 **59.** Domeneghetti, A., Castellarin, A. & Brath, A. Assessing rating-curve uncertainty and its effects on hydraulic model  
 338 calibration. *Hydrol. Earth Syst. Sci.* **16**, 1191–1202 (2012).
- 339 **60.** Knoben, W. J. M., Woods, R. A. & Freer, J. E. A quantitative hydrological climate classification evaluated with independent  
 340 streamflow data. *Water Resour. Res.* **54**, 5088–5109, <https://doi.org/10.1029/2018WR022913> (2018).

## 341 Acknowledgements

342 Frederik Kratzert was partially supported by a Google Faculty Research Award (PI: Sepp Hochreiter, JKU Linz). Daniel Klotz  
 343 was partially supported by Verbund AG. Martin Gauch was supported by the Linz Institute of Technology DeepFlood project.  
 344 We would like to thank Shaun Harrigan and Ervin Zsoter at ECMWF for help the ERA5-Land data product. We would also like  
 345 to thank Kurt Schwehr with the Google Earth Engine team for helping facilitate public access to the HydroATLAS dataset. This  
 346 work is a contribution to the large-sample hydrology working group of the Panta Rhei research initiative of the International  
 347 Association of Hydrological Sciences (IAHS).

## 348 Author Contributions Statement

349 All co-authors (F.K., G.N., N.A, T.E., M.G., O.G., L.G., A.H., D.K., S.N., G.S, Y.M.) were involved in developing the concept  
 350 for this dataset through extensive discussions about requirements, scope, and current data availability. F.K. wrote most of the  
 351 data processing code, T.E. wrote parts code for processing data on Earth Engine. G.N. did the trend analysis and comparison  
 352 between ERA5-Land and CAMELS-US. F.K. created all figures. All co-authors participated in writing the manuscript.

## 353 Competing Interests

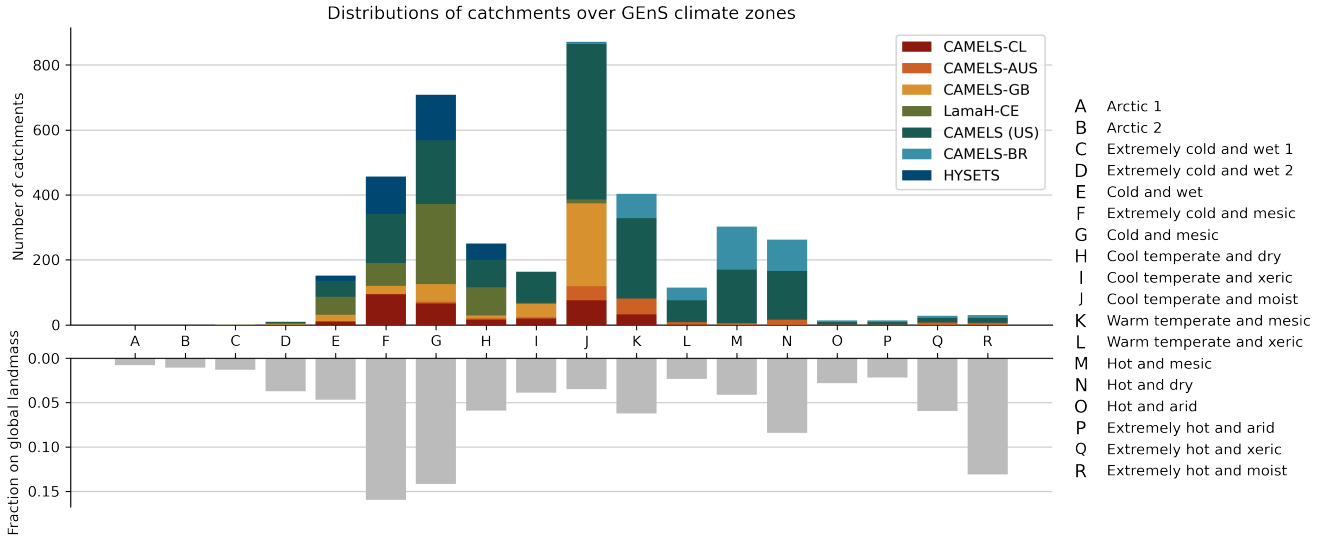
354 The authors declare no competing financial or professional interests.

## 355 Figures & Tables

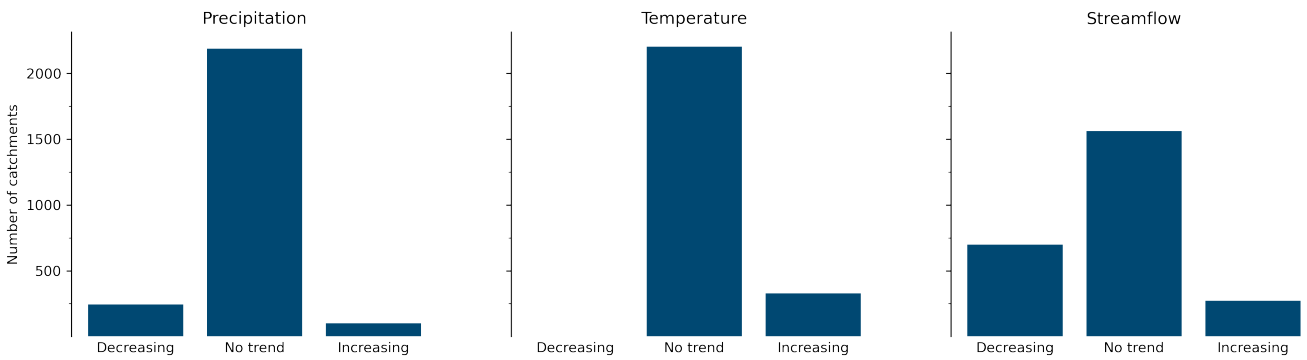
Feature (ERA5-Land variable name)	Aggregation	Unit
Precipitation (total_precipitation)	Daily sum	<i>mm/day</i>
Potential evaporation (potential_evaporation)	Daily sum	<i>mm/day</i>
Air temperature (temperature_2m)	Daily min/max and mean	$^{\circ}\text{C}$
Dew point temperature (dewpoint_temperature_2m)	Daily min/max and mean	$^{\circ}\text{C}$
Shortwave radiation (surface_net_solar_radiation)	Daily min/max and mean	$\text{Wm}^{-2}$
Net thermal radiation at the surface (surface_net_thermal_radiation)	Daily min/max and mean	$\text{Wm}^{-2}$
Surface pressure (surface_pressure)	Daily min/max and mean	<i>kPa</i>
Eastward wind component (u_component_of_wind_10m)	Daily min/max and mean	$\text{ms}^{-1}$
Northward wind component (v_component_of_wind_10m)	Daily min/max and mean	$\text{ms}^{-1}$

**Table 1.** ERA5-Land meteorological variables. Daily aggregates are computed in local time of each basin.

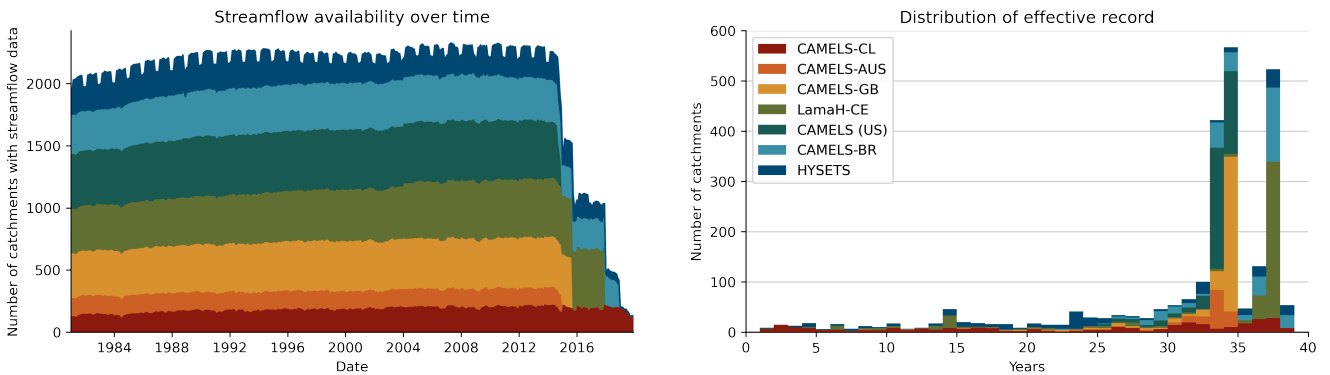




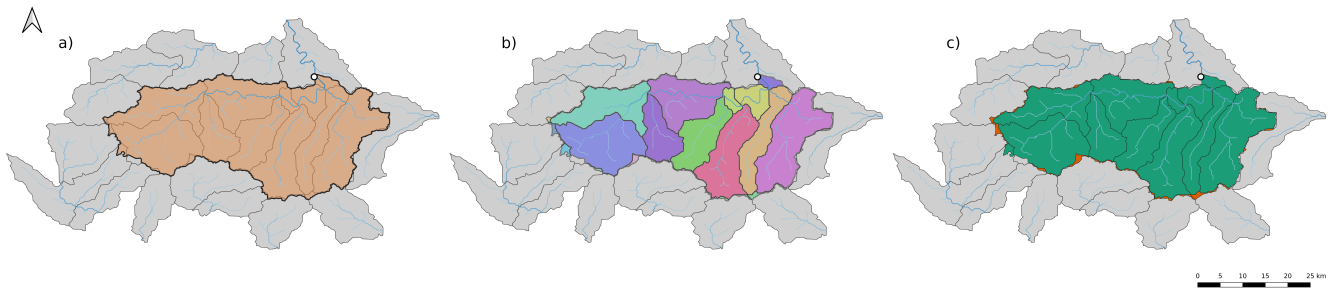
**Figure 1.** Distribution of the 2532 Caravan catchments among the Global Environmental Stratification (GENs) climate zones. The bottom part of the plots shows the fraction of a particular climate zone on the total land mass.



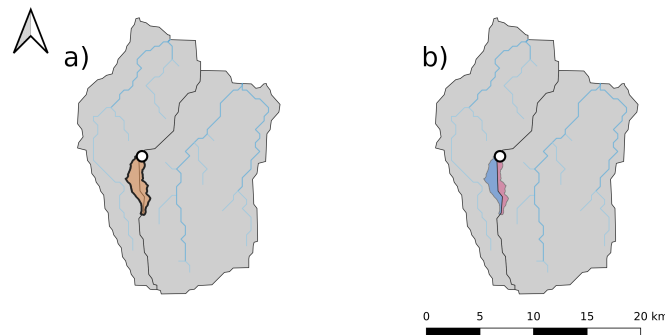
**Figure 2.** Number of catchments in Caravan (2532 basins over ~40 years of data) with statistically significant ( $\alpha = 0.05$ ) trends in three variables: mean temperature, precipitation, and discharge, assessed by an unmodified Mann-Kendall test. All data were averaged monthly before computing statistical trends.



**Figure 3.** Density of active Caravan gauge records through time (left) and distribution of water-years worth of data from each of 2532 basins in Caravan (right).



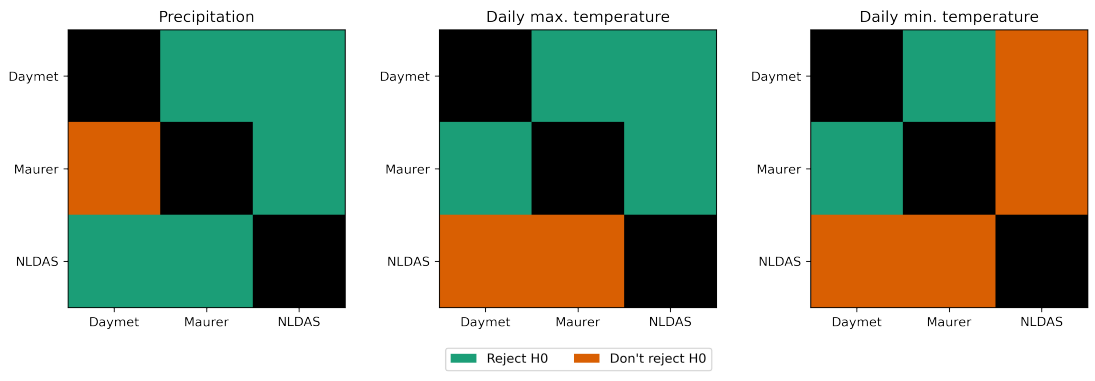
**Figure 4.** Visualization of the process of selecting HydroATLAS polygons for deriving catchment attributes for one randomly selected catchment. a) The orange polygon (bold outline) is the catchment of interest, as represented by a shapefile from one of the CAMELS datasets. Grey polygons (thin outlines) are HydroATLAS (level 12) polygons of the surrounding area. The white dot denotes the catchment outlet (gauge location) and blue lines denote the river network. b) Shows all HydroATLAS polygons or subsections of HydroATLAS polygons that intersect with the catchment polygon. Note that due to different underlying digital elevation maps, the boundaries of the polygons do not match perfectly. This leads to small intersection artifacts at catchment boundary. To alleviate this problem we excluded small polygons (smaller than 5km<sup>2</sup>) when deriving the area weighted catchment attributes from HydroATLAS. c) Shows the excluded (orange) intersecting polygons and the area used for deriving attributes (green).



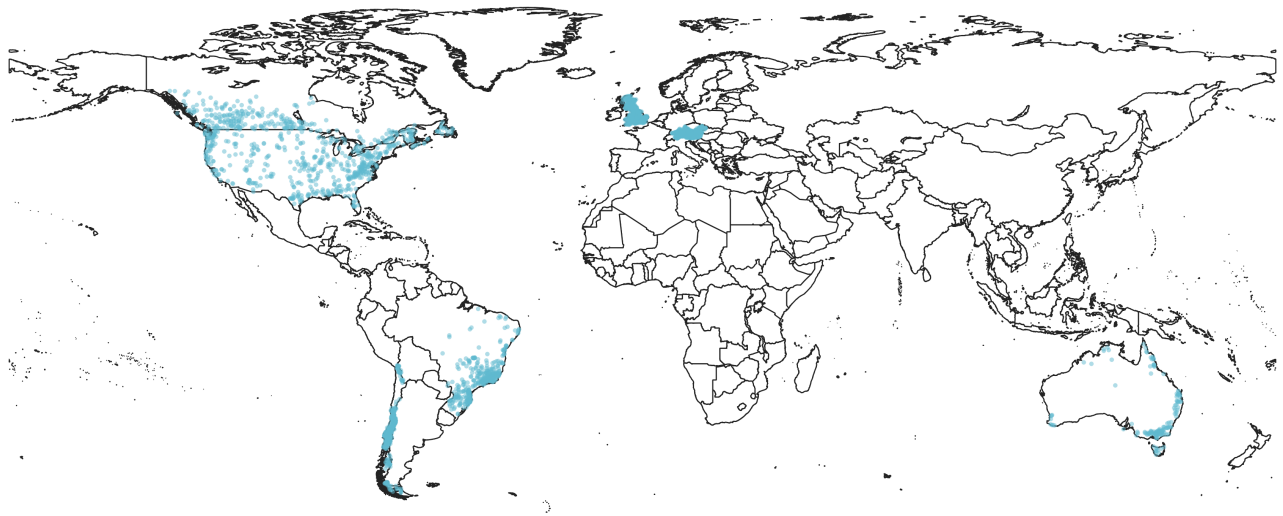
**Figure 5.** Example of small basin that was excluded from the dataset. a) The orange polygon (bold outline) denotes the catchment, the two grey polygons (thin outlines) are the surrounding HydroATLAS polygons, and the white dot denotes the catchment outlet. b) Shows the two intersecting areas of the HydroATLAS polygons with the catchment area. Both areas are a) smaller the minimum intersection area explained in Fig. 4 and b) from looking at the gauge location, it can be seen that the larger of the two intersections (blue) is in the neighboring HydroATLAS polygon that should not contribute when deriving the catchment attributes.

Feature (ERA5-Land variable name)	Aggregation	Unit
Snow water equivalent (snow_depth_water_equivalent)	Daily min/max and mean	mm
Soil water volume 0-7cm (volumetric_soil_water_layer_1)	Daily min/max and mean	m <sup>3</sup> /m <sup>3</sup>
Soil water volume 7-28cm (volumetric_soil_water_layer_2)	Daily min/max and mean	m <sup>3</sup> /m <sup>3</sup>
Soil water volume 28-100cm (volumetric_soil_water_layer_3)	Daily min/max and mean	m <sup>3</sup> /m <sup>3</sup>
Soil water volume 100-289cm (volumetric_soil_water_layer_4)	Daily min/max and mean	m <sup>3</sup> /m <sup>3</sup>

**Table 2.** ERA5-Land model state variables. Daily aggregates are computed in local time of each basin.



**Figure 6.** Results of one-way, paired t-tests with the null hypothesis ( $H_0$ ) that per-basin correlation coefficients between Caravan meteorological data and any given CAMELS-US meteorological data product (NLDAS, DayMet, Maurer) are not significantly lower than per-basin correlation coefficients between a given pair of CAMELS-US meteorological data products. The null hypothesis for the test in each grid cell compares correlations between Caravan and the CAMELS-US data product on the y-axis vs. correlations between the CAMELS-US data products on the x- and y-axes. Rejecting the null hypothesis indicates that the Caravan-related correlations are significantly lower than the correlations between the two CAMELS-US products ( $\alpha = 0.9$ )



**Figure 7.** Global distribution of catchments included in Caravan.

Group	Variable Name (HydroATLAS variable name)	Aggregation	Unit
Hydrology	Natural discharge (dis_m3_p_[mn, mx, yr])	annual min/max/mean	$m^3 s^{-1}$
	Land surface runoff (run_mm_syr)	annual mean at reach pour point	mm
	Inundation extent (inu_pc_s_[mn, mx, lt])	annual min/mean and long-term max	%
	Limnicity - percent lake area (lka_pc_sse)	spatial extent	%
	Degree of regulation (dor_pc_pva)	index at reach pour point	
	River area (ria_ha_ssu)		hectares
	River volume (ria_tc_ssu)		$10^3 m^3$
Physiography	Groundwater table depth (gwt_cm_sav)	spatial mean	cm
	Elevation (ele_mt_s_[av, mn, mx])	spatial mean/min/max	m above sea level
	Terrain slope (slp_dg_sav)	spatial mean	° (x10)
Climate	Stream gradient (sgr_dk_sav)	mean of reach segments	dm/km
	Climate zones from GENs (clz_cl_smj)	spatial majority	classes (n=18)
	Climate strata from GeNS (cls_cl_smj)	spatial majority	classes (n=125)
	Air temperature (tmp_dc_s_[01-12, mn, mx, yr])	monthly mean, annual mean/min/max	°C (x10)
	Precipitation (pre_mm_s_[01-2, yr])	monthly mean, annual mean	mm
	Potential evapotranspiration (pet_mm_s_[01-12, yr])	monthly mean, annual mean	mm
	Actual evapotranspiration (aet_mm_s_[01-12, yr])	monthly mean, annual mean	mm
	Global aridity index (ari_ix_sav)	spatial mean	index value (x10)
Land Cover	Climate moisture index (cmi_ix_s_[01-12, yr])	monthly mean, annual mean	index value (x10)
	Snow cover extent (snw_pc_s_[01-12, mx, yr])	monthly mean, annual max/mean	% cover
	Land cover classes (glc_cl_smj)	spatial majority	classes (n=22)
	Land cover extent (glc_pc_s01-22)	spatial mean	% cover
	Potential natural vegetation classes (pnv_cl_smj)	spatial majority	classes (n=15)
	Potential natural vegetation extent (pnv_pc_s01-15)	spatial mean	% cover
	Wetland classes (wet_cl_smj)	spatial majority	classes (n=12)
	Wetland extent (wet_pc_s01-09, g1, g2)	spatial mean	% cover & grouping
	Forest cover extent (for_pc_sse)	spatial mean	% cover
	Cropland extent (crp_pc_sse)	spatial mean	% cover
	Pasture extent (pst_pc_sse)	spatial mean	% cover
	Irrigated area extent (equipped) (ire_pc_sse)	spatial mean	% cover
	Permafrost extent (prm_pc_sse)	spatial mean	% cover
	Protected area extent (pac_pc_sse)	spatial mean	% cover
Soils & Geology	Terrestrial biomes	spatial majority	classes (n=14)
	Terrestrial ecoregions	spatial majority	classes (n=846)
	Freshwater major habitat types (fmh_cl_smj)	spatial majority	classes (n=13)
	Freshwater ecoregions	spatial majority	classes (n=426)
	Clay fraction in soil (cly_pc_sav)	spatial mean	%
	Silt fraction in soil (slt_pc_sav)	spatial mean	%
	Sand fraction in soil (snd_pc_sav)	spatial mean	%
Anthropogenic	Organic carbon content in soil (soc_th_sav)	spatial mean	tonnes/hectare
	Soil water content (swc_pc_s_01-12, yr)	monthly mean, annual mean	%
	Lithological classes (lit_cl_smj)	spatial majority	classes (n=16)
	Karst area extent (kar_pc_sse)	spatial mean	% cover
	Soil erosion (ero_kh_sav)	spatial mean	kg/hectare/yr
	Population count (pop_ct_ssu)		count (thousands)
	Population density (ppd_pk_sav)	spatial mean	people per $km^2$
Anthropogenic	Urban extent (urb_pc_sse)	spatial mean	% cover
	Nighttime lights (nli_ix_sav)	spatial mean	index value (x100)
	Road density (rdd_mk_sav)	spatial mean	$m/km^2$
	Human footprint (hft_ix_s_93,09)	spatial mean for 1993 & 2009	index value (x100)
	Gross domestic product (gdp_ud_sav)	spatial mean	USD (\$)
	Human development index (hdi_ix_sav)	spatial mean	index value (x1000)

**Table 3.** HydroATLAS catchment attributes.

Attribute	Description	Unit	Reference
p_mean	Mean daily precipitation	<i>mm/day</i>	
pet_mean	Mean daily potential evaporation	<i>mm/day</i>	
aridity	Aridity index, ratio of mean PET and mean precipitation	–	
frac_snow	Fraction of precipitation falling as snow	–	60
moisture_index	Mean annual moisture index in range [-1, 1], where -1 indicates water-limited conditions and 1 energy-limited conditions	–	60
seasonality	Moisture index seasonality in range [0, 2], where 0 indicates no changes in the water/energy budget throughout the year and 2 indicates a change from fully arid to fully humid.	–	60
high_prec_freq	Frequency of high precipitation days, where precipitation $\geq 5$ times mean daily precipitation	–	29
high_prec_dur	Average duration of high precipitation events (number of consecutive days where precipitation $\geq 5$ times mean daily precipitation)	days	29
low_prec_freq	Frequency of low precipitation days, where precipitation $< 1$ mmday <sup>-1</sup>	–	29
low_prec_dur	Average duration of low precipitation events (number of consecutive days where precipitation $< 1$ mmday <sup>-1</sup> )	days	29

**Table 4.** Climate attributes derived from ERA5-Land time series.