

1 Caravan - A global community dataset for 2 large-sample hydrology

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16 **ABSTRACT**

Hydrology relies on data, and high quality datasets are essential to support advances in hydrological process understanding and modelling. The past decade has seen the release of several large-sample hydrology (LSH) datasets. These datasets make available an easy-to-use combination of high-quality hydroclimatic time series (atmospheric and river flow data) plus biogeophysical attributes (e.g. topography, land cover, soil, geology and level of human interventions) for large samples (typically hundreds) of catchments. Many of these LSH datasets are named CAMELS (Catchment Attributes and Meteorology for Large-sample Studies). These LSH datasets have been widely adopted in academia and in industry, enabling (i) the systematic exploration of hydrological processes across hydroclimatic regions, (ii) benchmarking of hydrological models, and (iii) have accelerated the emergence of machine learning approaches for hydrology. However, LSH datasets are usually specific to a country or region, and there currently does not exist a global scale, publicly available, spatially consistent LSH dataset. This paper introduces a dataset called *Caravan* (a series of CAMELS) that (i) aggregates and standardizes seven existing datasets (including five CAMELS datasets) to set the foundation for a more global LSH dataset, and (ii) provides a cloud-based infrastructure with all code necessary to add new watersheds to this database. *Caravan* currently includes 2532 catchments spanning the most climatic regions, and provides daily time series of 15 hydroclimatic variables (observed streamflow plus land-surface variables from the ERA5-Land reanalysis) plus 210 catchment attributes (mostly from the HydroATLAS dataset). *Caravan's* open source, cloud-based software infrastructure allows members of the hydrology community to extend the dataset to new locations, and potentially to add new variables. Our vision is for *Caravan* to provide the foundation for a truly global open source community resource.

18 **Background & Summary**

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

23 Detailed datasets combining hydroclimatic time series, landscape attributes, and/or hydrological response variables like
24 streamflow exist for many experimental catchments, in many cases spanning decades¹⁻³. However, it is not possible to capture
25 the diversity of hydrological behavior from any individual watershed. In parallel, there also exist tens of thousands of gauges
26 monitoring rivers across the world. Although data available from these gauges are limited in that they do not describe all
27 of the hydrological processes in a given watershed, the large number of gauges means that they cover a wide range of
28 hydrological regimes and extreme events⁴⁻⁷. Gupta et al.⁸ argued that large sample sizes allow for assessment of the generality
29 of hydrological models and research findings. Large sample sizes also allow for large-scale research like detecting and
30 attributing systematic shifts in terrestrial water availability at regional^{9,10} to global scales^{11,12}. Moreover, large sample datasets

31 are necessary for developing generalizable data-driven models^{13–16}.

32 Recognizing this has led to the development of a sub-discipline in the hydrological sciences called *large-sample hydrology*
33 (LSH), which relies on data from hundreds to thousands of catchments¹⁷. There are an increasing number of publicly available
34 LSH datasets. Arguably, the first open LSH dataset was from the Model Parameter Estimation Experiment (MOPEX)¹⁸,
35 which contains data from 431 basins within the United States through 2003. Later datasets were developed for specific
36 countries or regions, including Australia¹⁹, Austria²⁰, Brazil²¹, North-America²², China²³, Chile²⁴, Europe²⁵, Great Britain²⁶,
37 Thailand²⁷, the United States^{28,29}, and the Arctic³⁰. Many of these are referred to as *Catchment Attributes and Meteorology for*
38 *Large-sample Studies (CAMELS)* datasets^{19,21,24,26,29}.

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)^{31,32}, which provides monthly and seasonal streamflow indices for 35,000+
41 locations, and the Global Runoff Data Base³³, 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 significantly³². On the other hand, HydroATLAS³⁴
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.,^{35,36}
48 for global model calibration or by Blöschl et al.³⁷ 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.¹⁷ 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.¹⁷ 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 standards³⁸.
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 zones³⁹, 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)²⁸
- 81 • 150 basins from CAMELS-AUS¹⁹

- 82 • 376 basins from CAMELS-BR²¹
- 83 • 314 basins from CAMELS-CL (using an updated Version from January 2022)²⁴
- 84 • 408 basins from CAMELS-GB²⁶
- 85 • 323 basins from HYSETS²²
- 86 • 479 basins from LamaH-CE²⁰

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 km² and smaller than 2000km², 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-Land⁴⁰. 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^{34,41} 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-US²⁹. 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 Engine⁴² 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.](https://doi.org/10.5281/zenodo.6578598)
146 [6578598](https://doi.org/10.5281/zenodo.6578598). 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 climate 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 from⁴⁰, however we used the Google Earth Engine repository. HydroATLAS attributes were derived from
175 the HydroATLAS dataset⁴³. Streamflow time series are collected from the respective region-specific repositories: Australia⁴⁴,
176 Brazil⁴⁵, Canada²², Chile⁴⁶, Great Britain⁴⁷, LamaH-CE (Austrian territory and Danube catchment up to Bratislava)⁴⁸, and the
177 United States:⁴⁹.

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 $100km^2$. 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^{50,51}, and usually involves intensive field campaigns^{52,53}, statistical
194 comparison between several data products^{54–56}, or modeling studies^{57,58} — 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 ?? 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.¹⁷ 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.6578598>.

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345 Author Contributions Statement

346 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
347 for this dataset through extensive discussions about requirements, scope, and current data availability. F.K. wrote most of the
348 data processing code, T.E. wrote parts code for processing data on Earth Engine. G.N. did the trend analysis and comparison
349 between ERA5-Land and CAMELS-US. F.K. created all figures. All co-authors participated in writing the manuscript.

350 Competing Interests

351 The authors declare no competing financial or professional interests.

352 Figures & Tables

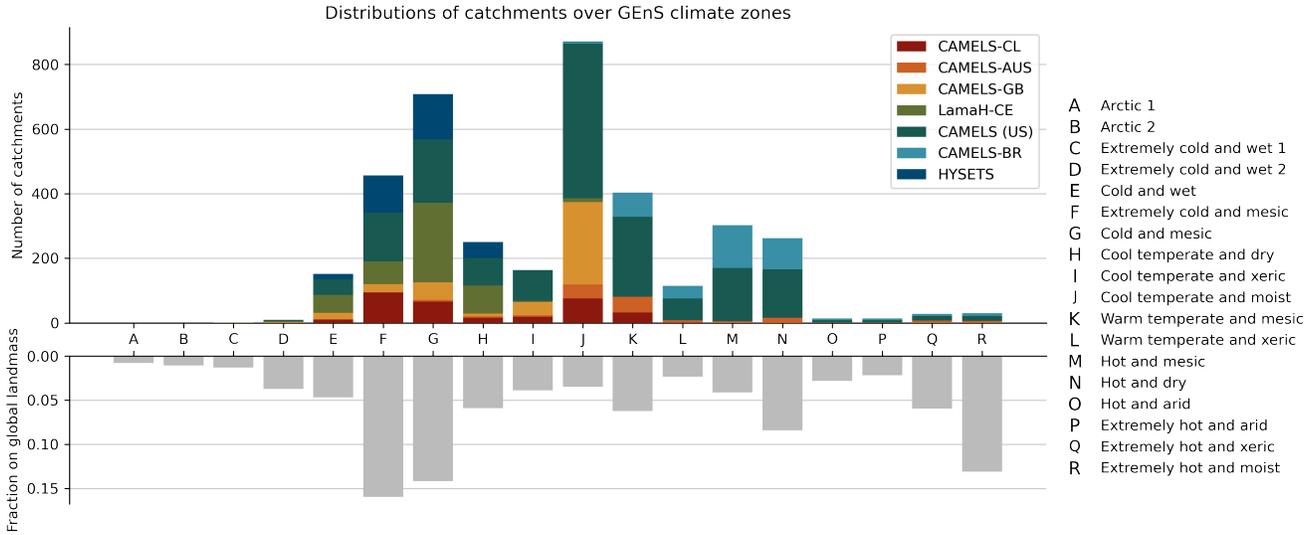


Figure 1. Distribution of the 2532 Caravan catchments among the Global Environmental Stratification (GENs) climate zones. The bottom part of the plots shows the fraction of a particular climate zone on the total land mass.

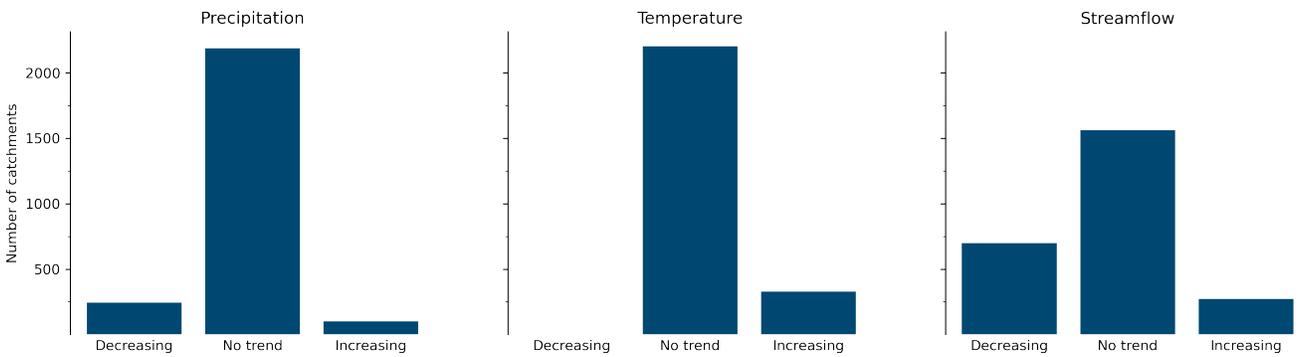


Figure 2. Number of catchments in Caravan (2532 basins over ~40 years of data) with statistically significant ($\alpha = 0.05$) trends in three variables: mean temperature, precipitation, and discharge, assessed by an unmodified Mann-Kendall test. All data were averaged monthly before computing statistical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

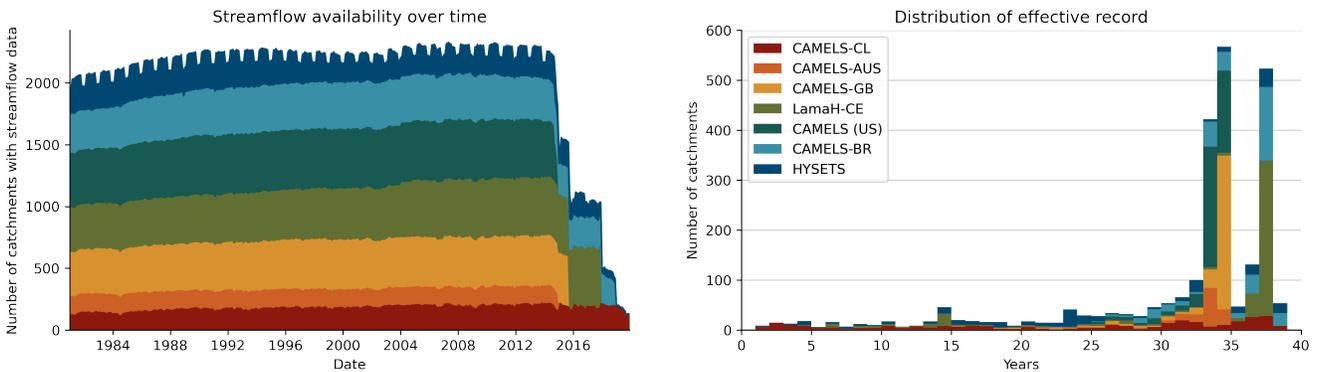


Figure 3. Density of active Caravan gauge records through time (left) and distribution of water-years worth of data from each of 2532 basins in Caravan (right).



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 5km²) when deriving the area weighted catchment attributes from HydroATLAS. c) Shows the excluded (orange) intersecting polygons and the area used for deriving attributes (green).

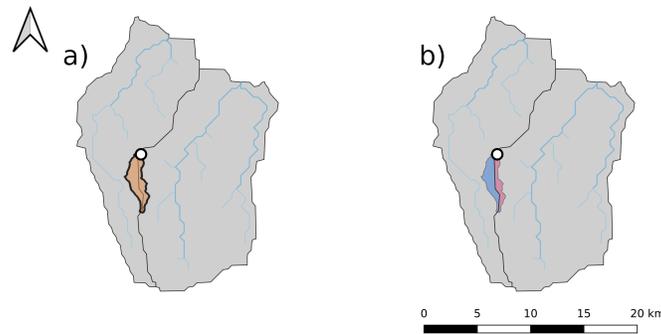


Figure 5. Example of small basin that was excluded from the dataset. a) The orange polygon (bold outline) denotes the catchment, the two grey polygons (thin outlines) are the surrounding HydroATLAS polygons, and the white dot denotes the catchment outlet. b) Shows the two intersecting areas of the HydroATLAS 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
Precipitation (total_precipitation)	Daily sum	mm/day
Potential evaporation (potential_evaporation)	Daily sum	mm/day
Air temperature (temperature_2m)	Daily min/max and mean	°C
Dew point temperature (dewpoint_temperature_2m)	Daily min/max and mean	°C
Shortwave radiation (surface_net_solar_radiation)	Daily min/max and mean	Wm ⁻²
Net thermal radiation at the surface (surface_net_thermal_radiation)	Daily min/max and mean	Wm ⁻²
Surface pressure (surface_pressure)	Daily min/max and mean	kPa
Eastward wind component (u_component_of_wind_10m)	Daily min/max and mean	ms ⁻¹
Northward wind component (v_component_of_wind_10m)	Daily min/max and mean	ms ⁻¹

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

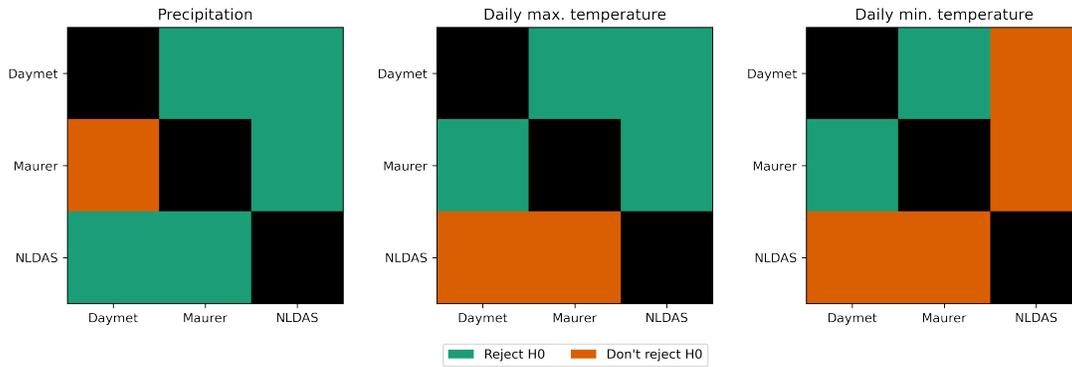


Figure 6. Results of one-way, paired t-tests with the null hypothesis (H_0) that per-basin correlation coefficients between Caravan meteorological data and any given CAMELS-US meteorological data product (NLDAS, DayMet, Maurer) are not significantly lower than per-basin correlation coefficients between 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 ($\alpha = 0.9$)

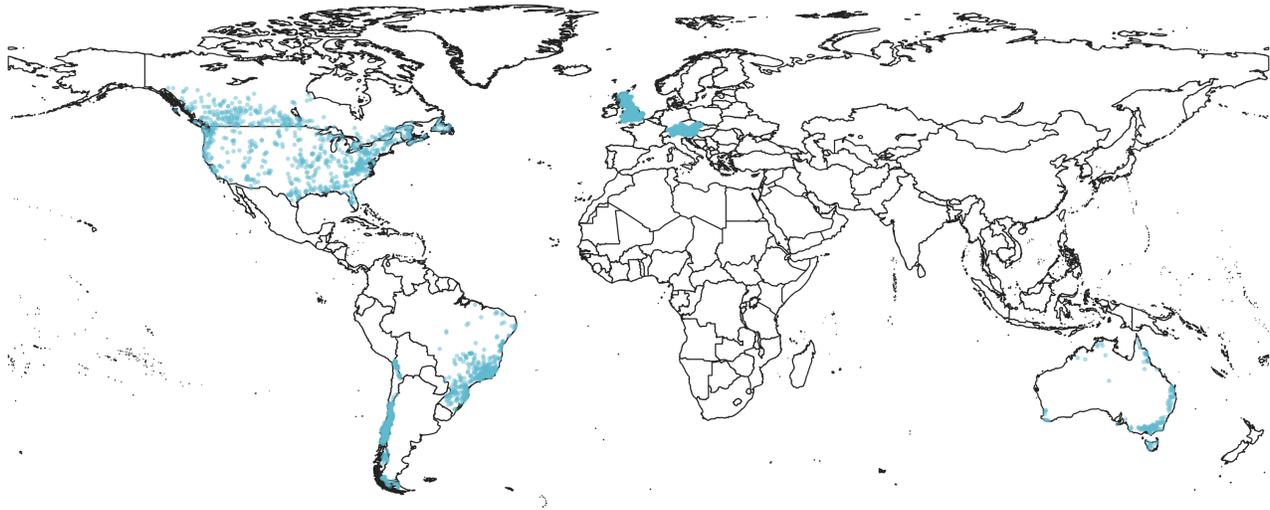


Figure 7. Global distribution of catchments included in Caravan.

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^3/m^3
Soil water volume 7-28cm (volumetric_soil_water_layer_2)	Daily min/max and mean	m^3/m^3
Soil water volume 28-100cm (volumetric_soil_water_layer_3)	Daily min/max and mean	m^3/m^3
Soil water volume 100-289cm (volumetric_soil_water_layer_4)	Daily min/max and mean	m^3/m^3

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

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	–	59
moisture_index	Mean annual moisture index in range [-1, 1], where -1 indicates water-limited conditions and 1 energy-limited conditions	–	59
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.	–	59
high_prec_freq	Frequency of high precipitation days, where precipitation ≥ 5 times mean daily precipitation	–	29
high_prec_dur	Average duration of high precipitation events (number of consecutive days where precipitation ≥ 5 times mean daily precipitation)	days	29
low_prec_freq	Frequency of low precipitation days, where precipitation < 1 mmday ⁻¹	–	29
low_prec_dur	Average duration of low precipitation events (number of consecutive days where precipitation < 1 mmday ⁻¹)	days	29

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