CAMELS-DE: hydro-meteorological time series and attributes for 1582 catchments in Germany

Ralf Loritz*[1], Alexander Dolich*[1], Eduardo Acuña Espinoza[1,A], Pia Ebeling[2,A], Björn Guse[3,4,A], Jonas Götte[5,6,7,A], Sibylle K. Hassler[8], Corina Hauffe[9,A], Ingo Heidbüchel[2,10,A], Jens Kiesel[3,11,A], Mirko Mälicke[1,A], Hannes Müller-Thomy[12,A] , Michael Stölzle[13,A], Larisa Tarasova[14,A]

*equal contribution, A alphabetic order

[1]Karlsruhe Institute of Technology (KIT), Institute for Water and Environment, Karlsruhe, Germany

[2]Helmholtz Centre for Environmental Research - UFZ, Department Hydrogeology, Leipzig, Germany

[3]Kiel University, Hydrology and Water Resources Management, Kiel, Germany

[4]German Research Centre for Geosciences - GFZ Potsdam, Section Hydrology, Potsdam, Germany

[5]WSL Institute for Snow and Avalanche Research SLF, Davos Dorf, Switzerland

[6]Climate Change, Extremes and Natural Hazards in Alpine Regions Research Center CERC, Davos Dorf

[7]Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland

[8]Karlsruhe Institute of Technology (KIT), Institute of Meteorology and Climate Research - Atmospheric Trace Gases and Remote Sensing (IMK-ASF), Karlsruhe, Germany

[9]University of Technology Dresden (TUD), Institute of Hydrology and Meteorology, Dresden, Germany

[10]Bayreuth Centre of Ecology and Environmental Research, University of Bayreuth, Bayreuth, Germany

[11]Stone Environmental, 535 Stone Cutters Way, 05602 Montpelier (VT), USA

[12]Technische Universität Braunschweig, Leichtweiß-Institute for Hydraulic Engineering and Water Resources, Division of Hydrology and River Basin Management, Braunschweig, Germany

[13]Chair of Hydrology, University of Freiburg, Freiburg, Germany, now at: LUBW Landesanstalt für Umwelt (State Agency for Environment), Karlsruhe, Germany

[14]Helmholtz Centre for Environmental Research - UFZ, Department Catchment Hydrology, Germany

Correspondence to: Ralf Loritz (Ralf.Loritz@kit.edu) and Alexander Dolich (Alexander.Dolich@kit.edu)

Abstract. Comprehensive large sample hydrological datasets, particularly the CAMELS datasets (Catchment Attributes and Meteorology for Large-sample Studies), have advanced hydrological research and education in recent years. These datasets integrate extensive hydro-meteorological observations with landscape features, such as geology and land use, across numerous catchments within a national framework. They provide harmonised large sample data for various purposes, such as assessing the impacts of climate change or testing hydrological models on a large number of catchments. Furthermore, these

datasets are essential for the rapid progress of data-driven models in hydrology in recent years. Despite Germany's extensive hydro-meteorological measurement infrastructure, it has lacked a consistent, nationwide hydrological dataset, largely due to its decentralised management across different federal states. This fragmentation has hindered cross-state studies and made the preparation of hydrological data labour-intensive. The introduction of CAMELS-DE represents a step forward in bridging this gap. CAMELS-DE includes 1582 streamflow gauges with hydro-meteorological time series data covering up to 70 years (median length of 46 years and a minimum length of 10 years), from January 1951 to December 2020. It includes consistent catchment boundaries with areas ranging from 5 to 15,000 km^2 along with detailed catchment attributes covering soil, land cover, hydrogeologic properties and data about human influences. Furthermore, it includes a regionally trained Long-Short Term Memory (LSTM) network and a locally trained HBV (Hydrologiska Byråns Vattenbalansavdelning) model that were used as quality control and that can be used to fill gaps in discharge data or act as baseline models for the development and testing of new hydrological models. Given the large number of catchments, including numerous relatively small ones (636 catchments < 100 km^2), and the time series length of up to 70 years (166 catchments with 70 years of discharge data), CAMELS-DE is one of the most comprehensive national CAMELS datasets available and offers new opportunities for research, particularly in studying long-term trends, runoff formation in small catchments and in analysing catchments with strong human influences.

1 Introduction

The CAMELS (Catchment Attributes and MEteorology for Large-sample Studies) datasets have become a cornerstone within the hydrological community for their comprehensive and consistent integration of hydro- and meteorological data across entire countries, including the USA, UK, Australia, Brazil, Chile, and others (e.g. Addor et al., 2017, Coxon et al., 2020). These datasets combine catchment attributes (e.g. land use, geology, and soil properties), hydrological time series (e.g. water level and discharge), and meteorological time series (e.g. precipitation and temperature) for a multitude of catchments typically within a single country. A distinctive feature of CAMELS datasets is their role as a benchmark for hydrological modelling and large sample analysis, enabling the comparison of hydrological models and the validation of water resources management strategies across diverse landscapes and climates (Brunner et al., 2021). Particularly the CAMELS-US dataset has thereby formed the basis for the on-going rise of machine learning methods in hydrology (e.g Kratzert et al., 2019).

Despite the widespread adoption and utility of CAMELS datasets in research, teaching, and practical applications globally, Germany with its extensive hydro-meteorological measurement network has no comprehensive and harmonised dataset yet. While there are large sample hydrological datasets that cover either parts of Germany (Klingler et al., 2021), only a fraction of the available national hydrological data (Färber et al., 2023), or focus on catchment water quality and thus cover a lower sampling frequency (Ebeling et al., 2022), the absence of a full CAMELS dataset that includes harmonised, daily, high-quality national hydrological and meteorological data together with catchment attributes and catchment boundaries derived from national and international products limits the potential for comprehensive analyses and advancements in hydrological research and practice. The CAMELS-DE data set addresses this gap (Dolich et al., 2024). CAMELS-DE compiles discharge, water levels, catchment attributes, and catchment boundaries together with a suite of meteorological time series and catchment attributes for 1582 catchments across Germany. Furthermore, the dataset includes discharge simulations from two sources: a regionally-trained Long-Short Term Memory (LSTM) network (Hochreiter & Schmidhuber, 1997; Hochreiter, 1998), and a locally trained conceptual HBV model (Hydrologiska Byråns Vattenbalansavdelning, Bergström and Forsman, 1973, Seibert, 2005, Feng et al., 2022). These simulations can serve as a benchmark for future hydrological modelling studies in Germany or help fill data gaps in hydrological time series. Each component of the CAMELS-DE processing pipeline is fully containerized (see section 7), which solves code dependency issues and generally contributes to the traceability, comprehensiveness, and reproducibility of the generation of CAMELS-DE. This study introduces not only a comprehensive dataset but also a suite of tools designed to generate reproducible hydrological datasets from the provided raw data. In the following sections we provide a comprehensive description of all data contained within CAMELS-DE including (1) its source data, (2) how the time series and attributes were produced, and (3) a discussion of the associated limitations and uncertainties. The structure of this paper (and also the corresponding dataset) closely mirrors that of the CAMELS-UK (Coxon et al., 2020) and CAMELS-CH (Höge et al., 2023) studies, ensuring comparability of the datasets while maintaining distinct elements that are not identical but closely related.

2 Data sources and providers

CAMELS-DE brings together hydrological data, consisting of daily measurements of discharge ($m^3 s^{-1}$) and water levels (m), from thirteen German federal state agencies, namely the Landesanstalt für Umwelt Baden-Württemberg (LUBW, Nomenclature of Territorial Units for Statistics (NUTS) Level 1: DE1), Bayerisches Landesamt für Umwelt (LfU-Bayern, DE2), Landesamt für Umwelt Brandenburg (LfU-Brandenburg, DE4), Hessisches Landesamt für Naturschutz, Umwelt und Geologie (HLNUG, DE7), Landesamt für Umwelt, Naturschutz und Geologie Mecklenburg-Vorpommern (LUNG MV, DE8), Niedersächsischer Landesbetrieb für Wasserwirtschaft, Küsten- und Naturschutz, Landesamt für Natur (NLWKN, DE9), Umwelt und Verbraucherschutz Nordrhein-Westfalen (LANUV NRW, DEA), Landesamt für Umwelt Rheinland-Pfalz (LUA-Rheinland Pfalz, DEB), Landesamt für Umwelt- und Arbeitsschutz Saarland (LUA, DEC), Landesamt für Umwelt, Landwirtschaft und Geologie Sachsen (LfULG, DED), Landesamt für Umweltschutz Sachsen-Anhalt (LAU, DEE), Landesamt für Landwirtschaft, Umwelt und ländliche Räume Schleswig-Holstein (LLUR, DEF), and Thüringer Landesamt für Umwelt, Bergbau und Naturschutz (TLUBN, DEG). The only federal states not included are the city-states of Bremen, Hamburg, and Berlin, which together account for less than 0.6 % of Germany's area, ensuring that the CAMELS-DE dataset remains representative for Germany.

Meteorological data, specifically precipitation, temperature, relative humidity and radiation, were obtained from the German Weather Service (DWD) from the HYRAS dataset (DWD-HYRAS, 2024). Spatially aggregated catchment attributes were obtained from various sources. From the European Union, we incorporated open-access datasets from Copernicus, the EU's Earth observation program, in particular the Copernicus GLO-30 DEM (Global 30-meter Digital Elevation Model; EU-DEM, 2022) for information about topography and the CORINE Land Cover 2018 dataset (CLC, 2018) for information about land cover. Soil attributes were derived from the global SoilGrids250m dataset (Poggio et al., 2021). Hydrogeological catchment attributes were derived from the "Hydrogeologische Übersichtskarte von Deutschland 1:250.000" (HGM250, 2019) provided by the Bundesanstalt für Geowissenschaften und Rohstoffe (BGR) while information about human influences, e.g. dams or weirs, was sourced from Speckhann et al. (2021).

3 Catchments

For CAMELS-DE, we sourced discharge (m^3 s^{-1}), water level data (m) and metadata for 2964 gauges and water level stations from the different federal state agencies (see section 2). We created a subset of the data by selecting only measurement stations that contained all required information, such as gauge name, location and catchment area in their metadata (n = 2700 stations), have at least a total of 10 years of discharge data, which must not necessarily be continuous (n = 2227 stations), have a catchment area larger than 5 km² and smaller than 15,000 km² (n = 2586 stations), have a catchment area located entirely within the borders of Germany (n = 2298 stations) and where the derived catchment area does not differ more than 20 % from the reported value by the federal states (n = 2164 stations; see section 3.1). These requirements were established based on the following rationale: A minimum of 10 years of discharge data is necessary to ensure an adequate time series length for hydrological modelling and calculating hydrological signatures. The minimum catchment area of 5 km² was chosen to match the 1 x 1 km resolution of the precipitation raster product, ensuring that multiple raster cells intersect with the catchment boundary. The upper limit was set because catchments larger than 15,000 km² are predominantly influenced by human activities and often extend beyond Germany's borders, necessitating their exclusion. The 20 % discrepancy between derived and reported catchment areas was arbitrarily chosen as an acceptable threshold for mass balance errors. This threshold prevents the inclusion of catchments with significantly inaccurate delineations while avoiding the exclusion of too much data (see Fig. 2b). Catchments partially located outside Germany's borders were excluded to avoid complications with cross-border data, especially given the absence of open, high-quality meteorological data from the DWD beyond Germany's national borders from 1951 to 2020. These criteria resulted in a subset of 1582 gauges for the CAMELS-DE dataset, which provides a reliable representation of hydrological processes in Germany (Fig. 1c, d).

3.1 Catchment boundaries

Not all state authorities provided official catchment boundaries for their gauging stations, and the methods used by the federal states to derive these boundaries are not uniform and remain unclear. Therefore, we tested two different global catchment datasets, HydroSHEDS (Lehner et al., 2021) and MERIT Hydro (Yamazaki et al., 2019), to derive a consistent set of catchment boundaries across Germany for the CAMELS-DE dataset. For that we compared the catchment areas determined with HydroSHEDS and MERIT Hydro to the catchment areas reported by the state authorities. This comparison was possible because all federal states shared the area of the catchments while not always sharing the actual catchment boundaries. Overall, the comparison revealed that MERIT Hydro has lower errors between the reported and derived catchment areas compared to HydroSHEDS. Among other reasons, this is because MERIT Hydro derives the catchment boundaries directly at the gauge locations provided by the federal states (see section 3.2). The comparison between MERIT Hydro and HydroSHEDS was further supported by extensive manual assessments, involving the visual inspection of numerous catchments to evaluate their shapes and alignments in case the federal state provided the data. Consequently, MERIT Hydro was used for the derivation of catchment boundaries for CAMELS-DE. Note that the derivation of the catchment boundaries is a major source of uncertainty as the meteorological time series and the catchment attributes are dependent on the catchment boundaries. To minimise the uncertainty of the catchment delineation we only included catchments with a deviation of up to 20 percent from the catchment area reported by the federal agencies (Fig. 2b). We report the original catchment area as (area_metadata) and the MERIT-Hydro based area (area) in the table of topographic attributes (Table 2).

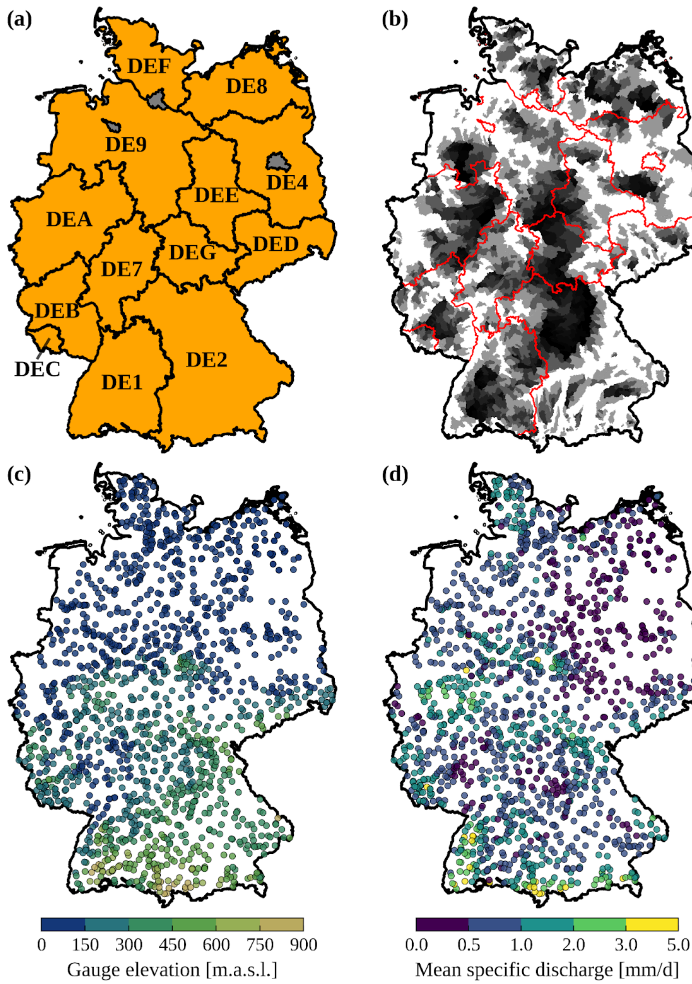

Figure 1: Panel (a) shows the German federal states labelled with their NUTS Level 1 ID as used for the CAMELS-DE gauge IDs. Panel (b) shows all 1582 catchments provided in CAMELS-DE, the geometries of the catchments are shown transparently, so a darker colour means that the geometries of the catchments in that area overlap; the darker the colour, the higher the density of catchments in that area. Panel (c) and panel (d) show the location of all 1582 gauging stations in CAMELS-DE; in panel (c) the locations are coloured according to the elevation of the gauging station, while in panel (d) the locations are coloured according to their mean specific discharge value. borders of Germany: © GeoBasis-DE / BKG (VG250, 2023)

3.2 Catchment boundaries derived from MERIT Hydro

MERIT (Multi-Error-Removed Improved-Terrain) Hydro was released by Yamazaki et al. (2019); providing a global hydrography dataset based on the MERIT DEM and various maps of water bodies (e.g. Global 3 arc-second Water Body Map by Yamazaki et al., 2017). It includes information such as flow direction, flow accumulation, adjusted elevations for hydrological purposes, and the width of river channels. The delineator.py package (Heberger, 2023) was used to delineate catchment boundaries. The method automatically derives catchment boundaries from the MERIT Hydro dataset based on the longitude and latitude of a gauging station and snaps the catchment pour point to the closest stream. Fig. 1b shows all derived CAMELS-DE catchments using MERIT Hydro within the German borders. The median catchment area within

CAMELS-DE is 129.1 km^2 (Fig. 2a). Compared to other CAMELS datasets, CAMELS-DE includes a large number of relatively small catchments with an area of less than 100 km^2 (i.e. 636 catchments, CAMELS-GB: 242 catchments, CAMELS-US: 142). Uncertainties in catchment delineation arise when comparing areas reported by federal states with those derived from MERIT Hydro, as shown in Fig. 2b, and these discrepancies are not uniformly distributed across Germany. They tend to be higher in flat lowland regions with minimal topography (Fig. 2c), particularly in the federal states to the north and east of Germany. Consequently, a large number of catchments are excluded from the CAMELS-DE dataset in the northern parts of Germany due to mismatches between reported and estimated areas. In the federal states of Brandenburg (DE4) and Mecklenburg-Western Pomerania (DE8), for example, we received 447 gauging stations, but given the uncertainty of the delineation in flat areas, only 277 of them showed a deviation of less than 20 percent from the reported area. In contrast, in the more mountainous state of Baden-Württemberg (DE1), 225 of 241 catchments met this criterion. As we report both the catchment areas provided by the federal states and those estimated by MERIT Hydro, the differences between these two measurements can be used to select or exclude catchments where there are significant uncertainties in the catchment shape and correspondingly in the derived static and dynamic attributes.

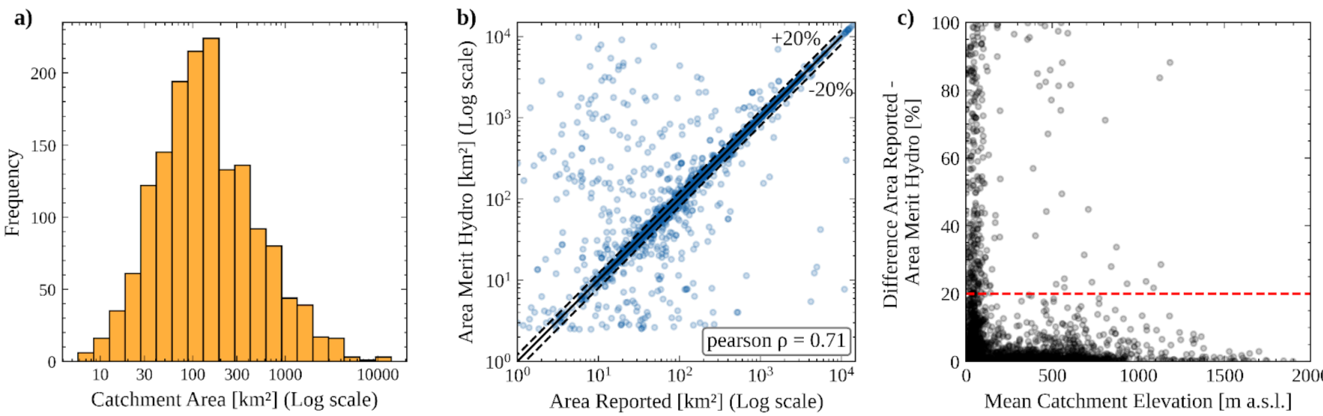

Figure. 2: Panel (a) shows the distribution of CAMELS-DE catchment areas on a logarithmic scale. Panel (b) shows the accuracy of catchment areas derived using MERIT Hydro compared to the area reported by the federal agencies; the dashed lines indicate ±20 percent error tolerance that was set for catchment selection. Panel (c) shows the absolute relative difference between the reported area by the federal states and the MERIT Hydro area against the mean catchment elevation. The red line marks the threshold of 20 percent allowed difference for the inclusion of a catchment in the CAMELS-DE dataset.

4 Time series

CAMELS-DE includes three sets of hydro-meteorological daily time series, as detailed in Table 1, covering the period from January 1, 1951, to December 31, 2020. These datasets are: (A) observed hydrologic time series (e.g., station discharge and water levels), (B) observed meteorologic time series (e.g., precipitation, temperature, humidity, and radiation), and simulated hydro-meteorologic time series (e.g., discharge simulated by a LSTM and a HBV model, including estimated evapotranspiration). Note that we do not include any information on evaporation in the non-simulated time series data, as we only include observation-based data here. However, a time series of potential evaporation based on the temperature-based

Hargreaves methodology is included in the simulated data (see section 6.2 for more details). However, due to the simplicity of the chosen approach, the potential evapotranspiration time series are highly uncertain, and one should exercise caution when using them.

All meteorological forcing data within CAMELS-DE are sourced from the HYRAS datasets, which are based on the interpolation of meteorological station data (DWD-HYRAS, 2024). This interpolation was conducted by the DWD (see subsection 4.1, 4.2, 4.3). The reliability of these datasets can be compromised by the individual interpolation methods employed (see section 4.1 to 4.3). In addition, inaccuracies in meteorological measurements can introduce uncertainties in the generated grid fields, especially given the extended timescale of 70 years, which may include changes in location and sensor types. Another source of uncertainty is the fact that the number of stations used in the interpolation process varies over time, mirroring changes in the measurement network. For example, the number of stations used for interpolating precipitation data fluctuates, starting at around 4500 in 1951, peaking at approximately 7500 in 2000, and then decreasing to approximately 5000 by 2020. In contrast, the number of stations used for radiation interpolation shows a consistent increase over the years, though the total number remains significantly lower, reaching about 900 stations by 2020. This uncertainty is crucial to consider when comparing data across different years, particularly if the focus is on a single or a few catchments in a certain area. Finally, we use the 'exact extract' method, which ensures that raster cells that are only partially covered are treated properly as they are weighted by the proportion of the cell that is covered, i.e. a raster cell that is only 20 % covered by the catchment is only weighted by 20 % when we aggregate to the spatial catchment mean (Fig. 3a illustrates partially covered cells at the catchment boundary). This is particularly important when deriving meteorological data for very small catchment areas. Although this approach also aids in comparing products with different resolutions, it is important to consider that the spatial resolution of the precipitation data, at 1 x 1 km, offers finer detail compared to the 5 x 5 km resolution used for temperature, humidity, and radiation data. This difference is crucial when comparing these datasets within smaller catchments.

4.1 Precipitation

CAMELS-DE utilises precipitation data (mm d^{-1}) with daily resolution, sourced from the HYRAS-DE-PRE dataset v5.0 (HYRAS-DE-PRE, 2022). We have calculated daily spatial minimum, mean, median, maximum, and standard deviation of the rainfall field over the catchment for each day. We estimated these statistical measures, rather than just the mean, because this allows us to capture spatial variations and patterns that can be crucial for event characterization or rainfall-runoff modelling, as illustrated in Fig. 3. The HYRAS-DE-PRE dataset v5.0 dataset is produced using the REGNIE interpolation method (Rauthe et al., 2013), which employs daily measured values from meteorological stations to generate an interpolated product on a 1x1 km grid. A detailed description of the interpolation method and the related uncertainties can be found in the official data description (HYRAS-DE-PRE, 2022).

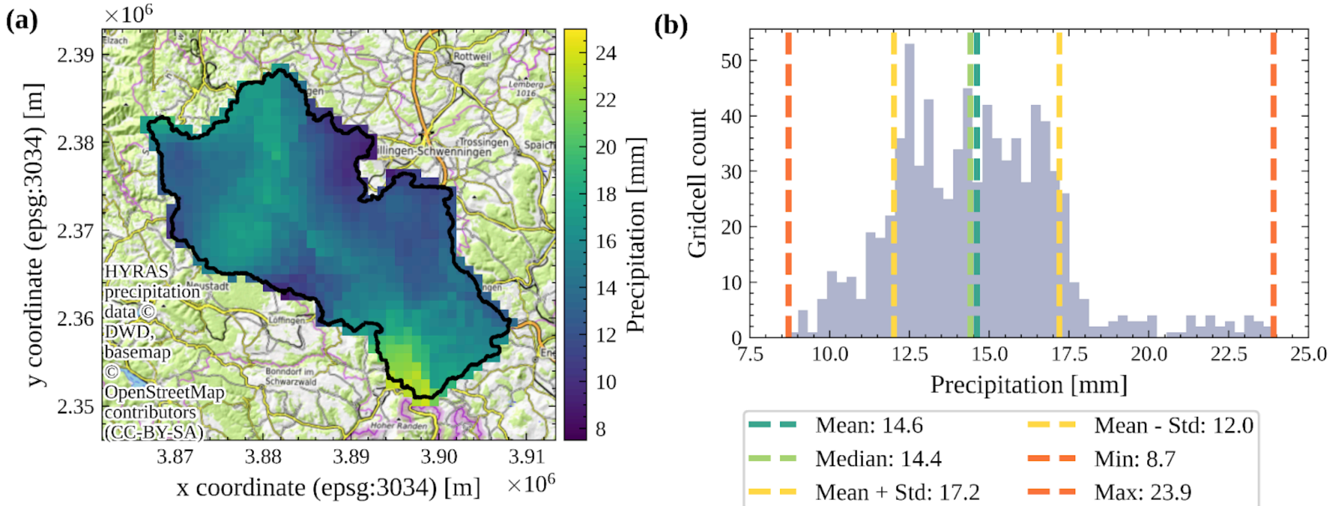

Figure 3: Panel (a) shows the catchment boundaries (black line) of the catchment Kirchen-Hausen in Baden-Württemberg overlayed by a clipped daily precipitation field from the HYRAS dataset on the date 1951-02-20. Panel (b) shows the spatial distribution of rainfall during the same high precipitation event as (a) over the catchment on 1951-02-20 and the statistical moments (mean, median, standard deviation, minimum and maximum) derived from the spatial distribution.

4.2 Temperature and relative humidity

CAMELS-DE employs daily temperature (°C) and relative humidity (%), derived from the HYRAS-DE-TAS (daily mean temperature, HYRAS-DE-TAS, 2022), TASMIN (daily minimum temperature, HYRAS-DE-TASMIN, 2022), TASMAX (daily maximum temperature, HYRAS-DE-TASMAX, 2022), and HURS (daily average relative humidity, HYRAS-DE-HURS, 2022) datasets v5.0, which cover the period from 1951 to 2020 on a 5 km x 5 km grid. This includes the spatial mean, median, and standard deviation of temperature from HYRAS-DE-TAS, alongside the spatial minimum and maximum temperatures from TASMIN and TASMAX, respectively. Additionally, for humidity, we integrate daily minimum, mean, median, maximum, and standard deviation values across the catchment area. The temperature and humidity data is based on interpolated station values (Razafimaharo et al., 2020). This interpolation method involves a nonlinear regression at each time step, aiming to estimate regional vertical temperature profiles across 13 subregions. These subregions are delineated based on criteria such as weather divides, proximity to the coast, and the extent of north-south variation. A detailed description of the interpolation method and the related uncertainties can be found in the corresponding data descriptions (HYRAS-DE-TAS, (2022); HYRAS-DE-TASMIN, (2022); HYRAS-DE-TASMAX, (2022); HYRAS-DE-HURS, (2022)).

4.3 Radiation

The CAMELS-DE dataset utilises daily mean global radiation data (in W m^{-2}) derived from the HYRAS-DE-RSDS datasets v3.0 (HYRAS-DE-RSDS, 2023), that covers a period from 1951 to 2020 with a 5 km x 5 km grid. We have derived daily, spatial minimum, mean, median, maximum, and standard deviation of the radiation field over the catchment for each day. The global radiation (RSDS) dataset integrates station measurement data (including sunshine duration and global radiation), satellite data, and ERA5 data (Muñoz-Sabater et al., 2021). A detailed description of the interpolation method and the related uncertainties can be found in the official data description (HYRAS-DE-RSDS, 2023).

4.4 Discharge and water levels

Observed discharge and water level data were requested from 13 state agencies (see section 2) as time series recorded at the gauging stations (Tab. 1). The number of stations with daily discharge data available per year increases in time from 187 on 1 January 1951 to a maximum of 1486 between November 2010 and February 2011 (Fig. 4a). The number of stations with water level data is generally lower, starting at 110 stations on 1 January 1951 and reaching a maximum of 1471 stations between March 2015 and December 2015. The time series span a maximum of 70 years, with each measuring station providing at least 10 years of data between January 1951 and December 2020 (Fig. 4b). These 10 years do not need to be consecutive but typically are. The median time series length of discharge is 46 years, while the median time series length of water level is 40 years. There is a sharp drop-off in Fig. 4a of 137 stations without data from 2017 to 2018 as the provided data from NLWKN (Lower Saxony, DE9) only range until the end of 2017. Another anomaly in Fig. 4a is the drop immediately followed by a rise in the year 2020, which is due to the fact that all measuring stations in Rhineland-Palatinate (DEB) show a gap in the discharge data from 10 February 2020 to 15 February 2020 and in the water level data from 13 February 2020 to 15 February 2020. No explanation could be found for this gap. The remaining data after the gap was manually quality controlled by visual inspection of the observed and simulated time series and no reason to exclude this data was found. In total, CAMELS-DE includes 156 stations for which the entire temporal range of 70 years of discharge data is available and for which a maximum of 2 percent of the data is missing in this period. There are 85 stations where this is the case for water level data.

4.5 Discharge and water levels - quality control

The quality control of all discharge and water level data was conducted by the respective federal states (quality controlled data was requested). However, the specific methods employed in this quality control are neither the same across the states, nor are they documented in some cases. Typically, quality control entails that a technical clerk has visually inspected the hydrological time series data. To account for this uncertainty we conducted an additional review of all time series data for high negative values and unrealistically high outliers and replaced such data points with not-a-number (NaN) values. We were conservative in these cases and only deleted values that were clear data errors to not remove potential extreme flood events from the time series. This adjustment was necessary in 8 catchments and is documented in the processing pipeline to assure reproducibility. Please note that negative discharge values are still possible in the CAMELS-DE dataset due to the influence of the tide in the northern part of Germany or due to human influences related to water resources management. Moreover, we assessed the hydro-meteorological time series using both a hydrological model and a data-driven model. This analysis helped us identify catchments with weak correlations between meteorological conditions and hydrological responses as well as catchments in which the mass balance is far from being closed. All catchments that exhibited a low model performance of the HBV model were subjected to manual visual inspection, resulting in the removal of 14 catchments (for more details we refer to section 6).

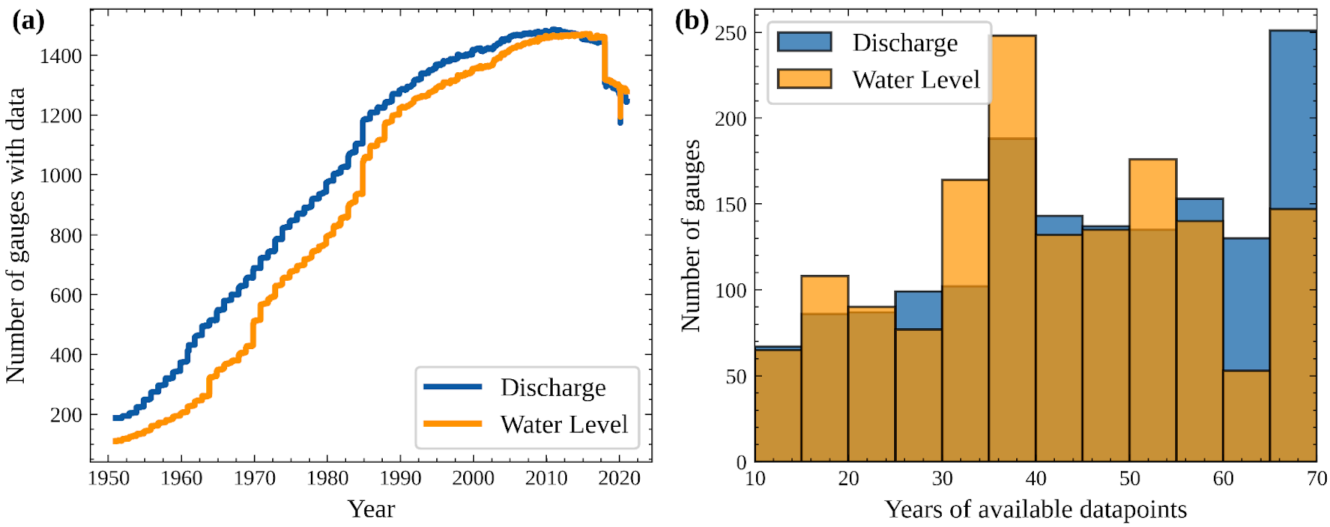

Figure 4: Panel (a) shows the number of gauging stations with available discharge (blue) and water level data (orange) in the period from 1951 to 2020, taking into account data gaps, i.e. the data must actually be available at the respective time. Panel (b) shows a histogram of the years of available data points for all measuring stations, i.e. the length of the time series minus eventual gaps in the time series.

Table 1: Catchment-specific hydro-meteorological variables available as daily time series in CAMELS-DE

Time series class	Time series name	Description	Unit	Data source
Hydrologic time series (1 Jan 1951–31 Dec 2020)	discharge_vol	Observed catchment discharge calculated from the water level and gauge geometry	$m^3 s^{-1}$	Federal state agencies (see section 2)
	discharge_spec	Observed catchment-specific discharge (converted to millimetres per day using catchment areas described in section 3.1)	$mm\ d^{-1}$	
	water_level	Observed daily water level	m	
Meteorologic time series (1 Jan 1951–31 Dec 2020)	precipitation_mean, precipitation_median, precipitation_min, precipitation_max, precipitation_stdev	Observed interpolated spatial mean, median, minimum, maximum and standard deviation of the daily precipitation (original resolution 1x1 km^2)	$mm\ d^{-1}$	German Weather Service HYRAS (DWD-HYRAS, 2024)
	temperature_min	Observed interpolated spatial mean daily minimum temperatures (original resolution 5x5 km^2)	°C	
	temperature_mean	Observed interpolated spatial mean daily mean	°C	

		temperatures (original resolution 5x5 km^2)		
	temperature_max	Observed interpolated spatial mean daily maximum temperatures (original resolution 5x5 km^2)	°C	
	humidity_mean, humidity_median, humidity_min, humidity_max, humidity_stdev	Observed interpolated spatial mean, median, minimum, maximum and standard deviation of the daily humidity (original resolution 5x5 km^2)	%	
	radiation_global_mean, radiation_global_median, radiation_global_min, radiation_global_max, radiation_global_stdev	Observed interpolated spatial mean, median, minimum, maximum and standard deviation of the global radiation (original resolution 5x5 km^2)	W m^2	
Simulated hydrologic time series (1 Jan 1951–31 Dec 2020)	pet_hargreaves	Daily mean of potential evapotranspiration calculated using the Hargreaves equation	mm d^{-1}	Regional LSTM model, HBV model and Hargreaves equation for potential evapotranspiration (see section 6, https://github.com/KIT-HYD/Hy2DL/tree/v1.1, last access: 24 July 2024)
	discharge_vol_obs	Observed volumetric discharge	m^3 s^{-1}	
	discharge_spec_obs	Observed catchment-specific discharge	mm d^{-1}	
	discharge_vol_sim_lstm	Volumetric discharge calculated from discharge_spec_sim_lstm and the catchment area	m^3 s^{-1}	
	discharge_spec_sim_lstm	Catchment-specific discharge simulated with the LSTM (see section 6)	mm d^{-1}	
	discharge_vol_sim_hbv	Volumetric discharge calculated from discharge_spec_sim_hbv and the catchment area	m^3 s^{-1}	
	discharge_spec_sim_hbv	Catchment-specific discharge simulated with the HBV model (see section 6)	mm d^{-1}	
	simulation_period (training, validation, testing)	Flag indicating the simulation period in which the daily value is contained (training, validation, testing)	–	

5 Catchment attributes

In addition to the daily time series of hydro-meteorological variables available in CAMELS-DE, the dataset also includes a series of static catchment attributes which are considered time-invariant and include information about topography (section 5.1), hydroclimatic signatures (section 5.2) and catchment attributes covering land-cover (section 5.3), soil (section 5.4), hydrogeology (section 5.5) and human influences (section 5.6).

5.1 Location and topography

For CAMELS-DE, we developed a system of catchment IDs, since the official IDs used by the federal states are inconsistent beyond federal state boundaries. However, the official provider IDs are contained in the topographic attributes of the dataset

(Tab. 2). The gauge IDs in CAMELS-DE are based on the NUTS classification, which divides the EU territory hierarchically according to administrative boundaries. In Germany, the first hierarchical level NUTS 1 provides a code for each federal state (e.g. DE7 for Hessen, DED for Saxony; Fig. 1b). We assign an ID code to each gauge as follows. The ID of each gauge starts with the NUTS 1 code of the corresponding federal state. For each federal state the gauges are coded in arbitrary order starting from 10000 for the first gauge and adding a step of 10 for each following gauge (e.g. DE710000 for the first station in Hessen, DE710010 for the second station, DE710020 for the third station, etc.). This system ensures consistency of the gauge IDs in Germany, and additionally provides the information about the federal state of each gauge. Topographic attributes such as the location (coordinate systems WGS84 and ETRS89), gauge elevation (m) and catchment area (km^2) were provided by the federal agencies, the area of the MERIT Hydro catchment is also provided. Additionally we derived the gauge point elevation (m) and basic statistical variables (min, mean, median, 5th and 95th percentile, max) of the catchment elevation (m) from the GLO-30 DEM. CAMELS-DE additionally provides the location of all gauging stations and catchment boundaries as a shape file and a geopackage file.

5.2 Climate and hydrology

For the CAMELS-DE dataset, we calculated long-term climatic and hydrological signatures in line with the attributes found in CAMELS-CH (covering the period between 1981–2020) and CAMELS-UK (covering the period between 1970–2015) with the difference that we cover the period from 1951–2021 (see Tab. 2). Both types of attributes are calculated based solely on complete hydrological years with respect to the discharge (1 October to 30 September of the following year; again inline with the definition of a hydrological year chosen in CAMELS-UK and CAMELS-CH), with a maximum tolerance of 5 % missing values per hydrological year, ensuring robustness in the data used for analysis. If a specific catchment has discharge data for only a limited number of hydrologic years, we calculate the climatic and hydrological indices for those same years to maintain consistency across all CAMELS datasets and across the climatic and hydrological attributes.

For each catchment, the hydrologic attributes include values for the mean specific discharge ($mm\ d^{-1}$), the runoff ratio, the start and end dates of available discharge data, the percentage of days on which discharge data is available (%), the slope of the flow duration curve between the log-transformed 33rd and 66th percentiles, the number of days after which the cumulative discharge since 1 October reaches half of the annual discharge (d), the 5th and 95th quantile of specific discharge ($mm\ d^{-1}$) and the frequency of high flow, low flow and zero flow days ($d\ yr^{-1}$) together with the average duration of high-flow and low-flow events (d). The climatic attributes are calculated on the basis of the HYRAS meteorological data for each catchment and include mean daily precipitation ($mm\ d^{-1}$), the seasonality of precipitation, the fraction of precipitation falling as snow, the frequency of high and low precipitation days ($d\ yr^{-1}$), the average duration of high precipitation events and dry periods (d) as well as the season during which most high and low precipitation days occur. The code to estimate the signatures in CAMELS-DE is based on the codes used to derive the signatures for CAMELS-US (https://github.com/naddor/camels, last access: 19 July 2024), CAMELS-UK and CAMELS-CH to assure compatibility.

5.3 Land cover

Land cover in CAMELS-DE is derived from the Corine Land Cover dataset (CLC, 2018) which provides consistent and thematically detailed information on land cover across Europe. The dataset was produced within the frame of the Copernicus Land Monitoring Service referring to land cover / land use status of the year 2018 and is based on the classification of satellite images (other major releases have been published in the years 1990, 2000, 2006, 2012). The CLC dataset from 2018 has a spatial resolution of 100 m for raster data. This ensures detailed and consistent land cover information across Europe. CAMELS-DE includes land cover percentages per catchment of the first hierarchical land cover level: artificial surfaces, agricultural areas, forests and semi-natural areas, wetlands and water bodies. The decision to not mix the hierarchical land cover levels ensures that uncertainties in classification due to varying levels of detail are minimised. Catchment shapes and codes to derive land cover classes of lower order or from different releases of CLC in a consistent manner with CAMELS-DE are delivered with the dataset (Dolich, 2024).

5.4 Soil

Soil attributes for CAMELS-DE are derived from the SoilGrids250m dataset (Poggio et al., 2021), which maps the spatial distribution of soil properties globally at six standard depths. The SoilGrids dataset is generated by training a machine learning model on approximately 240,000 locations worldwide, using over 400 global environmental covariates that describe vegetation, terrain morphology, climate, geology, and hydrology. For CAMELS-DE, we derived the mean values of the soil bulk density, soil organic carbon, volumetric percentage of coarse fragments and proportions of clay, silt and sand for each catchment. The resulting variables are aggregated from the six SoilGrid depths to the depths 0-30 cm, 30-100 cm and 100-200 cm by calculating a weighted mean. The accuracy of soil property models, as described by Poggio et al. (2021), is limited by the availability and quality of input data and the assumptions in the modelling process. For instance, discrepancies in how soil data are collected, analysed, and reported by different entities challenge efforts toward data standardisation and harmonisation. However, the relatively high number of observations in Germany reduces this uncertainty to a certain extent. Furthermore, the defined catchment boundaries allow for an assessment of the reported uncertainties within each catchment. If needed the catchment boundaries delivered with CAMELS-DE can be used to calculate the reported uncertainties of SoilGrids within each catchment.

5.5 Hydrogeology

The hydrogeological attributes for CAMELS-DE are derived from the hydrogeological overview map of Germany on the scale of 1:250,000; ”HÜK250” (HGM250, 2019), which describes the hydrogeological characteristics of the upper, large-scale contiguous aquifers in Germany. For CAMELS-DE, the areal percentage of the various HÜK250 classes (see Tab. 2) was calculated for each catchment, whereby the variables of the classes permeability, aquifer media type, cavity type, consolidation, rock type and geochemical rock type sum to 100 percent. Uncertainties in these data may arise from the generalisation required to scale point measurements to a gridded product, which can oversimplify complex hydrogeological features, potentially leading to inaccuracies in the representation of local variations and the spatial distribution of aquifer properties.

5.6 Human influence

CAMELS-DE includes information on human influences within catchments, primarily focusing on existing dams and reservoirs in Germany. This information is sourced from the inventory of dams in Germany (Speckhann et al., 2021), which offers detailed data including dam names, locations, associated rivers, years of construction and operation start, crest lengths, dam heights, lake areas, lake volumes, purposes (such as flood control or water supply), dam structure types, and specific building characteristics for 530 dams across Germany. For catchments containing multiple dams, this data is aggregated to provide a comprehensive overview. Specifically, CAMELS-DE includes key information about the dams within each catchment, such as the number of dams, the names of the dams, the rivers where these dams are located, the operational years of the oldest and newest dams, the total area and volume of all dam lakes at full capacity, and the overall purposes of these dams. It is important to note that the "Inventory of Dams in Germany" does not claim to be exhaustive. The absence of recorded dams in this inventory does not necessarily indicate a lack of human influence within a catchment. Nearly all catchments in Germany experience substantial anthropogenic influences, and it is likely that some dams, weirs, or reservoirs (particularly smaller ones) are not documented in the dataset. Another relevant indicator of human influence included in CAMELS-DE is hence the proportion of artificial and agricultural surfaces derived from land cover attributes (see section 5.3).

6 Benchmark LSTM and HBV model

CAMELS-DE, in addition to hydro-meteorological observations and catchment attributes, includes results from data-driven and conceptual lumped rainfall-runoff simulations for each catchment. More specifically, these results are derived from a regionally trained LSTM network (trained on all catchments at the same time) and a locally trained lumped HBV model (trained at each individual catchment; Bergström and Forsman, 1973, Seibert, 2005, Feng et al., 2022). These models serve three main purposes: (a) they are used to identify catchments where the relationship between meteorological forcing and streamflow is difficult to capture (low model performance), indicating possible strong human influences such as dams or reservoirs, or potential issues with the catchment delineation or the streamflow or meteorological time series; (b) they can serve as a benchmark for future modelling studies based on CAMELS-DE in a sense that the reported performance values and time series can be used as a baseline model and (c) in case of a good model performance can be used to fill missing values of the observed discharge time series. Both models were trained over the period from October 1, 1970, to December 31, 1999, validated from October 1, 1965, to September 30, 1970, and tested from January 1, 2000, to December 31, 2020. CAMELS-DE includes the simulated discharges for both models for the entire 70 years (Tab. 1), a flag was added to indicate if the corresponding time step was used in training, validation or testing. In the following we explain the model setups and analyse the simulation results in detail. The code of the LSTM model and the HBV model were carefully tested and benchmarked (Acuña Espinoza et al., 2024). The codes have been designed to allow easy access and a permalink to the code version used for CAMELS-DE can be found here (https://github.com/KIT-HYD/Hy2DL/tree/v1.1, last access: 24 July 2024).

6.1 Setup LSTM model

The LSTM uses mean precipitation, standard deviation of precipitation, mean radiation, mean minimum temperature and mean maximum temperature as dynamic (time varying) input features and specific discharge as a target variable. Static features and hyperparameters were set according to the study of Acuña et al. (2024) with modifications made to (1) an increased hidden size from 64 to 128 and (2) a reduced number of epochs from 30 to 20. The remaining hyperparameters were set as follows: number of hidden layers = 1; learning rate = 0.001; dropout rate = 0.4; batch size = 256; sequence length = 365 days; iterative optimization algorithm = Adam. We use the basin-averaged Nash-Sutcliffe Efficiency (NSE∗) loss function proposed by Kratzert et al. (2019) to avoid an imbalance during training due to the higher influence of catchments with a higher runoff generation. In addition, to the model results (see Tab. 2), we provide the model training epochs of the regional LSTM as part of the CAMELS-DE dataset.

6.2 Setup HBV model

The lumped HBV model used in CAMELS-DE is a variant of the well-known HBV (Hydrologiska Byråns Vattenbalansavdelning; Bergström and Forsman, 1973) model. A detailed description of the model architecture and setup can be found in the studies by Seibert (2005) and Feng et al. (2022). HBV uses mean precipitation and potential evapotranspiration (E_{pot}; mm d^{-1}) as inputs. The E_{pot} is calculated using the temperature-based Hargreaves formula, detailed by Adam et al. (2006) and based on earlier work by Droogers and Allen (2002), as explained and cited in Clerc-Schwarzenbach et al. (2024). This variant of the Hargreaves formula resulted in the lowest mass balance error in most catchments with respect to other methods (e.g. Penman, Priestly Taylor) to estimate evapotranspiration and was additionally chosen due to its low data requirements, enabling the utilisation of HYRAS precipitation and temperature data to generate the E_{pot} time series with a limited number of assumptions. The E_{pot} time series are included in CAMELS-DE (Tab. 2) for the entire time period of 70 years. In terms of model calibration, the SHM was trained individually for each basin using the NSE as a loss function, employing the Differential Evolution Adaptive Metropolis (DREAM; Vrugt, 2016) algorithm as implemented in the SPOTPY (SPOTting model parameters using a ready-made PYthon package, Houska et al., 2015) library. In contrast to the LSTM, the SHM model is mass conserving and hence more sensitive to errors in the catchment delineation that can lead to mass balance errors (see section 3). The difference between the SHM and the LSTM performance can be seen as an indicator either for a strong human influence or for an imprecise catchment delineation as the LSTM can create mass. In addition to the model results (see Tab. 2), we provide the HBV model parameters for each catchment as part of the CAMELS-DE dataset.

6.3 Results LSTM and SHM model

In this section, we focus our analysis on the LSTM and SHM model in catchments where at least 20 % of the daily data is available during the 30-year training period and 10 % during the testing period, covering a total of 1411 catchments. The median performance of the LSTM, as quantified by the NSE during the testing period, is 0.84 across 1411 catchments. Of these, 94 catchments have an NSE lower than 0.5 (6.66 % of all catchments), out of which 28 have a negative NSE (1.98 % of all catchments). For the 94 catchments with NSE below 0.5, most streamflow time series exhibit a low Pearson correlation with daily precipitation (< 0.1) and these catchments are often considerably affected by the construction and/or operation of dams or flood control structures (human influences attributes). Therefore, model performance of the LSTM network can be used to identify catchments that are subject to considerable uncertainties, either due to measurement inaccuracies or significant human influences.

Fig. 5a illustrates the performance of the LSTM model across various federal states, with relatively consistent results across the board except for the federal states of Brandenburg (DE4) and Saxony-Anhalt (DEE). In Brandenburg, lowland catchments characterised by sandy soils, considerable groundwater impacts, abundance of natural lakes and human constructed weirs, canals and cross-connections between streams most likely yield a distinctly lower model performance compared to the rest of the German federal states. Besides the federal state of Brandenburg and Saxony-Anhalt the analysis of the LSTMs simulations reveals no clear correlation between the model performance and the topographic attributes (e.g., area), climatic attributes (e.g., long-term mean precipitation), or hydrological attributes (e.g., long-term mean flow).

The performance of HBV is with a median NSE of 0.72 lower than that of the LSTM (Fig. 5b). In 192 catchments (13.61 %) the HBV shows a performance below a NSE of 0.5 and in 44 (3.12 %) a performance below a NSE of 0. The spatial patterns of performance measured by the NSE are consistent between the LSTM and HBV. In other words, catchments where the LSTM performs well are typically also accurately represented by HBV, and vice versa, as illustrated in Fig. 5e. Catchments in which HBV significantly underperforms compared to the LSTM are almost invariably strongly influenced by human-made structures such as dams or weirs, or they are located in areas with uncertain catchment delineation. We propose that the HBV model, which conserves mass and uses time-invariant parameters, struggles to adapt to dynamic changes in catchment function caused by human activities that result in inaccuracies in water flow and storage due to structures like dams, weirs or due to irrigation or pumping. A hypothesis that requires further testing in the few catchments where this is the case.

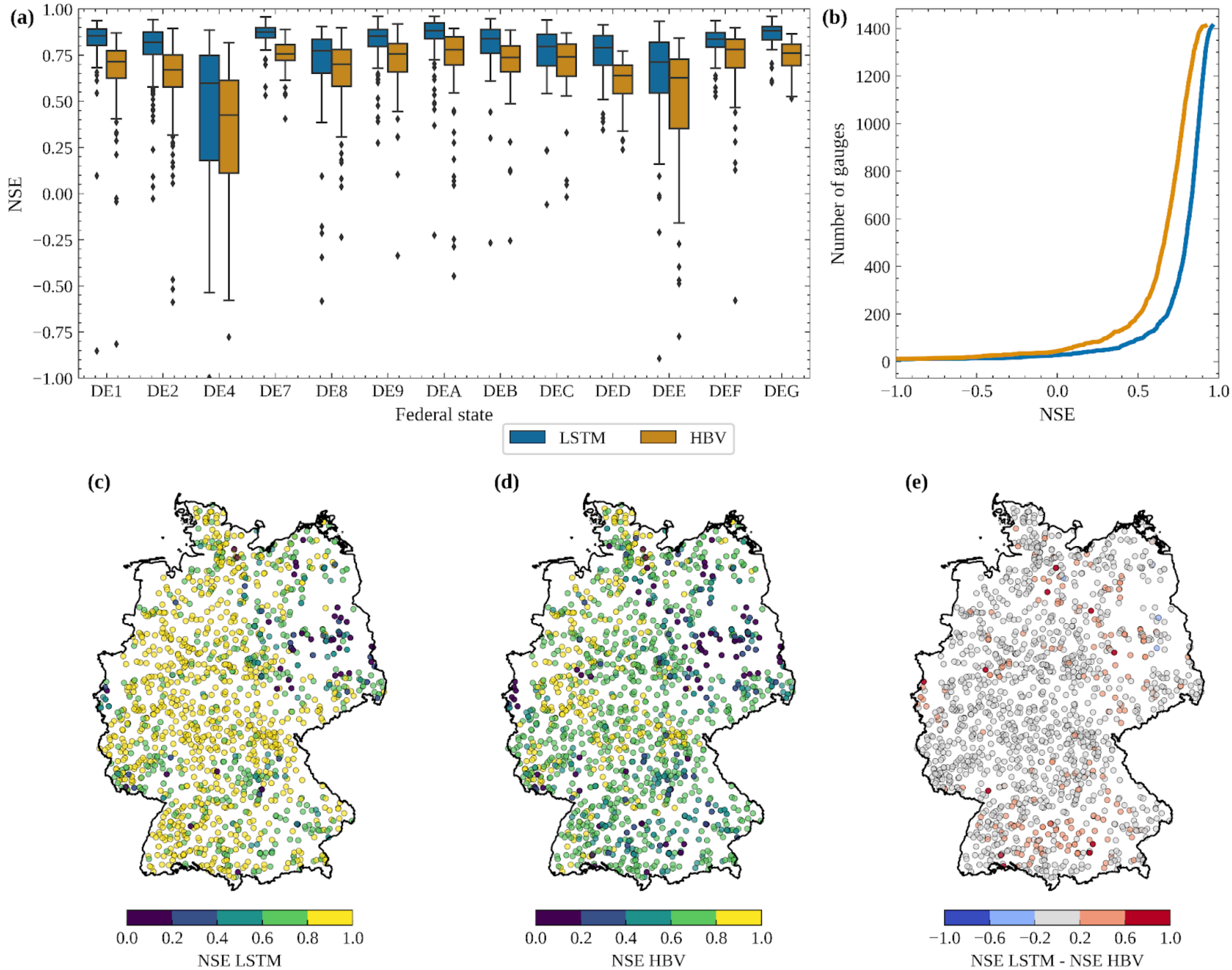

Figure 5: Panel (a) shows boxplots visualising the distribution of the NSE of the LSTM network (blue) and the HBV model (orange) for each federal state in Germany for the testing period. Panel (**b**) shows a cumulative plot of the NSE for the general comparison of the LSTM model and the HBV model. Panel (c) shows the NSE values of the LSTM for 1411 gauging stations in Germany, while panel (c) shows the same for the NSE values of the HBV model. Panel (e) shows the difference between the NSE values of the LSTM and the HBV model for all gauging stations in Germany, borders of Germany: © GeoBasis-DE / BKG (VG250, 2023)

7 Code availability, reproducibility and extensions

The processing of CAMELS-DE is structured in a modular manner to enhance the clarity and reproducibility of the processing pipeline. The CAMELS-DE processing pipeline was published separately with more details and permalinks to the released repository versions that represent the code state that was used to process and compile CAMELS-DE (Dolich, 2024).

For each component of CAMELS-DE, a distinct GitHub repository was established. Within each repository, a dedicated Docker container was developed to process specific input datasets (e.g. HYRAS, GLO-30 DEM). Containerization is particularly well-suited for this project as it ensures that each component of the data processing pipeline runs consistently across different computing environments. This containerization simplifies dependency management, enhances reproducibility, and facilitates the deployment and version control of each processing module. Fig. 6 illustrates the architecture of the processing pipeline, where each blue block represents an individual GitHub repository equipped with a Docker container that processes the yellow input data to produce the green output data. All repositories are uniformly structured, and the accompanying documentation provides detailed descriptions of each repository, guidelines for building and running the Docker containers, including the necessary folder mounts, and instructions for accessing the required input data. In the initial phase of the CAMELS-DE data processing pipeline, raw discharge and water level data, along with station metadata provided by the federal states, are processed and harmonised. Subsequently, MERIT-Hydro catchment boundaries are delineated for each station, a pivotal step since all further datasets depend extensively on these catchment boundaries. Meteorological time series data for these catchments are then processed to compute statistics such as area mean and median. Following this, attributes such as soil properties, hydrogeology, land cover, topography, and human influences are derived for each catchment (see Table 2). In the final stage, all derived data are integrated and formatted according to the established structure of the CAMELS-DE dataset, mirroring the organisational schema of CAMELS-GB or CAMELS-CH.

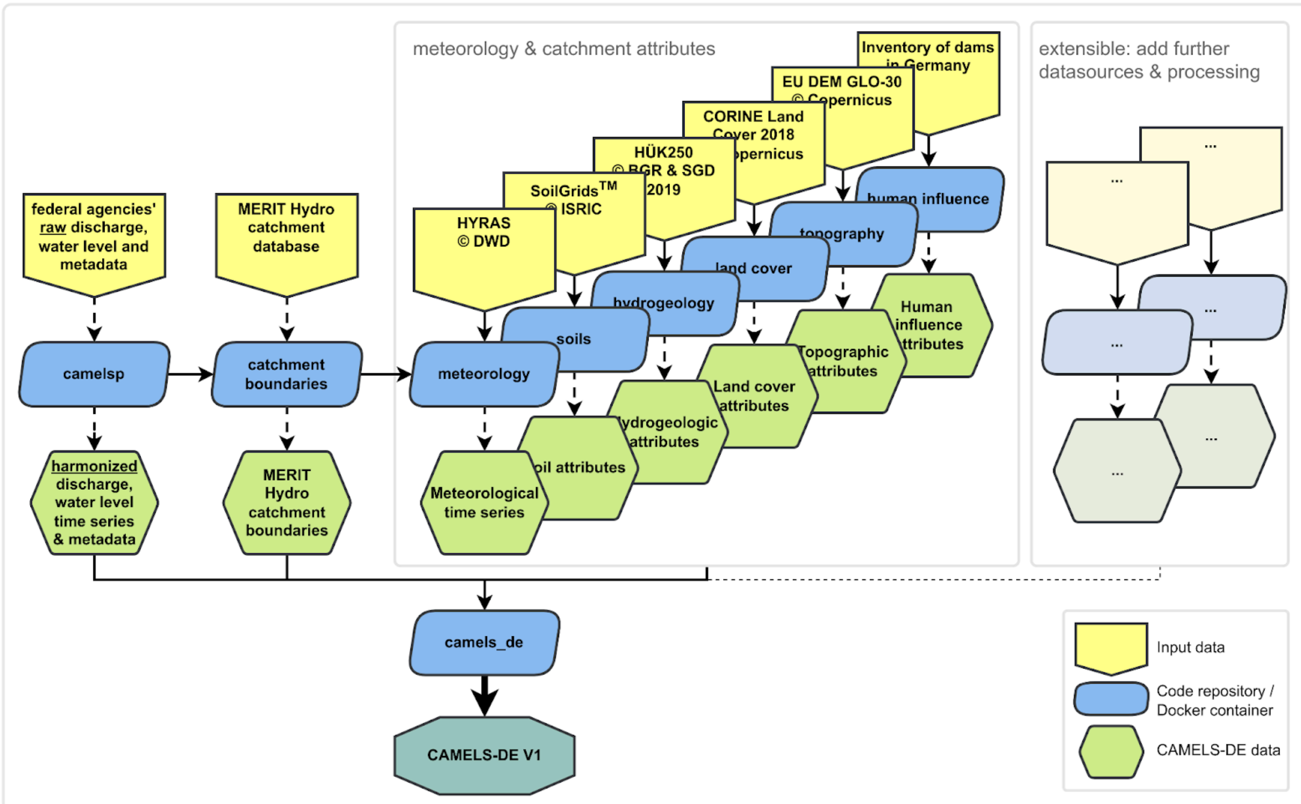

Figure 6: Diagram of the CAMELS-DE data processing pipeline. Starting with raw discharge and metadata harmonisation, it proceeds to derive MERIT-Hydro catchment boundaries. Subsequent processing includes meteorological data extraction and aggregation followed by the extraction of various catchment attributes. In the final step, all extracted data sources are integrated in the structured CAMELS-DE dataset, consistent with CAMELS-GB or CAMELS-CH (Dolich, 2024).

The modular design of the CAMELS-DE processing pipeline enhances its traceability, comprehensibility, and reproducibility, differing significantly from a monolithic code approach that compiles the entire dataset into a single repository. This structure not only facilitates the extension of the pipeline to incorporate additional data sources, especially further catchment attributes, without the need to re-run or rewrite the entire system but also allows for the adaptation of processing or aggregation methods and the seamless release of updated versions of the CAMELS-DE dataset. The publicly available Docker containers and the code within them serve not only as a comprehensive guide to understanding the data processing methods used in CAMELS-DE but also provide a foundation for further data processing using the catchment geometries included in the dataset. We encourage researchers to enrich CAMELS-DE with additional data sources and explore ways to enhance the baseline model results. Such contributions are invaluable for continuous improvements and expansions of the CAMELS-DE dataset, reflecting our commitment to advancing hydrological research and applications through reproducible science.

8 Data availability

This manuscript describes the state of version 1.0 of CAMELS-DE, which is freely available at https://doi.org/10.5281/zenodo.13837553 (Dolich et al., 2024), accompanied by a comprehensive data description. The code to reproduce CAMELS-DE can be found at https://doi.org/10.5281/zenodo.12760336 (Dolich, 2024).

9 Conclusions

CAMELS-DE is a significant step forward in hydrological research for Germany and beyond, offering a comprehensive dataset that spans 1582 catchments with hydro-meteorological daily time series from 1951 to 2020. CAMELS-DE includes detailed catchment delineations and properties, such as reservoir data, land-use, soils, and hydrogeology, which are all vital to analyse and describe the local and regional hydrology of Germany. Furthermore, CAMELS-DE includes simulations from a regionally trained LSTM and locally trained HBV model that can be used either to fill gaps in discharge data in case of good model performance or act as baseline models for the development and testing of new hydrological models. Due to the length of the provided time series of up to 70 years CAMELS-DE opens up new opportunities for investigating long-term hydrological trends or conducting large-sample studies across diverse catchments, including a large number of catchments smaller than 100 km². The dataset's modular design, achieved through the containerization of each processing component, ensures that the data processing is traceable, comprehensible, and reproducible. This approach makes it easier to extend the dataset by incorporating new data sources, adapting processing methods, and releasing updated versions without the need to re-run the entire pipeline. While CAMELS-DE serves as a useful benchmark for large sample hydrology, we invite the scientific community to enrich it with additional data sources and improved methods. In conclusion, CAMELS-DE aims to support a broad range of hydrological research and applications, to foster better understanding and management of water resources in Germany and beyond and to contribute to future global hydrological studies.

Author contribution: RL and MS initiated the CAMELS-DE project. AD prepared and processed data, created most figures and wrote together with RL most of the manuscript. All other authors suggested improvements and made additions to the manuscript, as well as provided data and expertise for specific topics.

Competing interests: At least one of the (co-)authors is a member of the editorial board of Earth System Science Data or Hydrology and Earth System Sciences.

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Table 2.: Catchment-specific static attributes available in CAMELS-DE

Attribute class	Attribute name	Description	Unit	Data source
Location and topography	gauge_id	catchment identifier based on the NUTS classification as described in section 5.1 e.g. DE110000, DE110010, …	–	Federal state agencies (see section 2)
	provider_id	official gauging station ID assigned by the federal states	–	
	gauge_name	gauging station name		
	water_body_name	water body name	–	
	federal_state	federal state in which the measuring station is located		
	gauge_lon	gauging station longitude (EPSG:4326)	°	
	gauge_lat	gauging station latitude (EPSG:4326)	°	
	gauge_easting	gauging station easting (EPSG:3035)	m	
	gauge_northing	gauging station northing (EPSG:3035)	m	
	gauge_elev_metadata	gauging station elevation as given by the federal states	m.a.s.l.	
	area_metadata	catchment area as given by the federal states	km²	
	gauge_elev	gauging station elevation derived from the GLO-30 DEM	m a.s.l.	Copernicus GLO-30 DEM (EU-DEM, 2022)
	area	catchment area derived from the MERIT Hydro catchment	km²	
	elev_mean	mean elevation in the catchment based on the MERIT Hydro geometry	m a.s.l.	
	elev_min	minimum elevation within catchment	m a.s.l.	
	elev_5	5th percentile elevation within catchment	m a.s.l.	
	elev_50	median elevation within catchment	m a.s.l.	
	elev_95	95th percentile elevation within catchment	m a.s.l.	

	elev_max	maximum elevation within catchment	m a.s.l.	
Climate	p_mean	long-term mean of daily precipitation from 1951 to 2020	mm d^{-1}	German Weather Service HYRAS (DWD-HYRAS, 2024)
	p_seasonality	seasonality and timing of precipitation (estimated using sine curves to represent the annual temperature and precipitation cycles, positive (negative) values indicate that precipitation peaks in summer (winter), and values close to zero indicate uniform precipitation throughout the year).	–	
	frac_snow	fraction of precipitation falling as snow, i.e. while mean air temperature is < 0° C	–	
	high_prec_freq	frequency of high-precipitation days (≥ 5 times mean daily precipitation)	d yr^{-1}	
	high_prec_dur	mean duration of high-precipitation events (number of consecutive days ≥ 5 times mean daily precipitation)	d	
	high_prec_timing	season during which most high-precipitation days occur, e.g. 'jja' for summer. If two seasons register the same number of events a value of NA is given.	season	
	low_prec_freq	frequency of dry days (< 1 mm d^{-1})	d yr^{-1}	
	low_prec_dur	mean duration of dry periods (number of consecutive days < 1 mm d^{-1} mean daily precipitation)	d	
	low_prec_timing	season during which most dry season days occur, e.g. 'son' for autumn. If two seasons register the same number of events a value of NA is given.	season	
Hydrology	q_mean	mean daily specific discharge	mm d^{-1}	Federal state agencies (see section 3.1) and German Weather Service HYRAS (DWD-HYRAS, 2024)
	runoff_ratio	runoff ratio (ratio of mean daily discharge to mean daily precipitation)	–	
	flow_period_start	first date for which daily streamflow data is available	–	
	flow_period_end	last day for which daily streamflow data is available		
	flow_perc_complete	percentage of days for which streamflow data is available from Jan 1951–31 Dec 2020	%	
	slope_fdc	slope of the flow duration curve (between the log-transformed 33rd and 66th stream flow percentiles, see Coxon et al. (2020)	–	
	hfd_mean	mean half-flow date (number of days since 1.	d	

		Oct at which the cumulative dis charge reaches half of the annual discharge)		
	Q5	5 % flow quantile (low flow)	mm d^{-1}	
	Q95	95 % flow quantile (high flow)	mm d^{-1}	
	high_q_freq	frequency of high-flow days ((> 9 times the median daily flow)	d yr^{-1}	
	high_q_dur	mean duration of high-flow events (number of consecutive days > 9 times the median daily flow)	d	
	low_q_freq	frequency of low-flow days (< 0.2 times the mean daily flow)	d yr^{-1}	
	low_q_dur	mean duration of low-flow events (number of consecutive days < 0.2 times the mean daily flow)	d	
	zero_q_freq	fraction of days with zero stream flow	–	
Land cover	artificial_surfaces_perc	areal coverage of artificial surfaces	%	CORINE Land Cover 2018 (CLC, 2018)
	agricultural_areas_perc	areal coverage of agricultural areas	%	
	forests_and_seminatural_areas_perc	areal coverage of forests and semi-natural areas	%	
	wetlands_perc	areal coverage of wetlands	%	
	water_bodies_perc	areal coverage of water bodies	%	
Soil	clay_0_30cm_mean clay_30_100cm_mean clay_100_200cm_mean	weight percent of clay particles (< 0.002 mm) in the fine earth fraction at depths 0 - 30 cm, 30 - 100 cm and 100 - 200 cm	wt. %	SoilGrids250m (Poggio et al., 2021)
	silt_0_30cm_mean silt_30_100cm_mean silt_100_200cm_mean	weight percent of silt particles (≥ 0.002 mm and ≤ 0.05/0.063 mm) in the fine earth fraction at depths 0 - 30 cm, 30 - 100 cm and 100 - 200 cm	wt. %	
	sand_0_30cm_mean sand_30_100cm_mean sand_100_200cm_mean	weight percent of sand particles (> 0.05/0.063 mm) at depths 0 - 30 cm, 30 - 100 cm and 100 - 200 cm	wt. %	
	coarse_fragments_0_30cm_mean coarse_fragments_30_100cm_mean coarse_fragments_100_200cm_mean	volumetric fraction of coarse fragments (> 2 mm) at depths 0 - 30 cm, 30 - 100 cm and 100 - 200 cm	vol %	
	soil_organic_carbon_0_30cm_mean soil_organic_carbon_30_100cm_mean soil_organic_carbon_100_200cm_mean	soil organic carbon content in the fine earth fraction at depths 0 - 30 cm, 30 - 100 cm and 100 - 200 cm	g kg^{-1}	

	bulk_density_0_30cm_mean bulk_density_30_100cm_mean bulk_density_100_200cm_mean	bulk density of the fine earth fraction at depths 0 - 30 cm, 30 - 100 cm and 100 - 200 cm	kg dm^{-3}	
Hydrogeology	aquitard_perc aquifer_perc aquifer_aquitard_mixed_perc	areal coverage of aquifer media type classes	%	HÜK250 © BGR & SGD (Staatlichen Geologischen Dienste) 2019 (HGM, 2019)
	kf_very_high_perc (>1E-2 m s^{-1}) kf_high_perc (>1E-3 – 1E-2 m s^{-1}) kf_medium_perc (>1E-4 – 1E-3 m s^{-1}) kf_moderate_perc ((>1E-5 – 1E-4 m s^{-1}) kf_low_perc (>1E-7 – 1E-5 m s^{-1}) kf_very_low_perc (>1E-9 - 1E-7 m s^{-1}) kf_extremely_low_perc (<1E-9 m s^{-1}) kf_very_high_to_high_perc (>1E-3 m s^{-1}) kf_medium_to_moderate_perc (>1E-5 – 1E-3 m s^{-1}) kf_low_to_extremely_low_perc (<1E-5 m s^{-1}) kf_highly_variable_perc kf_moderate_to_low_perc (>1E-6 – 1E-4 m s^{-1})	areal coverage of permeability classes	%	
	cavity_fissure_perc cavity_pores_perc cavity_fissure_karst_perc cavity_fissure_pores_perc	areal coverage of cavity type classes	%	
	consolidation_solid_rock_perc consolidation_unconsolidated_rock_perc	areal coverage of consolidation classes	%	
	rocktype_sediment_perc rocktype_metamorphite_perc rocktype_magmatite_perc	areal coverage of rock type classes	%	
	geochemical_rocktype_silicate_perc geochemical_rocktype_silicate_carbonatic_perc geochemical_rocktype_carbonatic_perc geochemical_rocktype_sulfatic_perc geochemical_rocktype_silicate_organic_components_perc geochemical_rocktype_anthropogenically_modified_through_filling_perc geochemical_rocktype_sulfatic_halitic_perc geochemical_rocktype_halitic_per	areal coverage of geochemical rock type classes	%	

	c			
	waterbody_perc	areal coverage of water body areas according to hydrogeological map	%	
	no_data_perc	percentage of areas with missing data	%	
Human influence	dams_names	names of all dams located in the catchment	–	Inventory of dams in Germany (Speckhann et al., 2021)
	dams_river_names	names of the rivers where the dams are located	–	
	dams_num	number of dams located in the catchment	–	
	dams_year_first	year when the first dam entered operation	–	
	dams_year_last	year when the last dam entered operation	–	
	dams_total_lake_area	total area of all dam lakes at full capacity	km^2	
	dams_total_lake_volume	total volume of all dam lakes at full capacity	Mio m^3	
	dams_purposes	purposes of all the dams in the catchment	–	
Hydrological Simulations	training_perc_complete	percentage of observed specific discharge values in the training period (1970-10-01 – 1999-12-31) that are not NaN	%	Regional LSTM model, HBV model (see section 6, https://github.com/KIT-HYD/Hy2DL/tree/v1.1, last access: 24 July 2024)
	validation_perc_complete	percentage of observed specific discharge values in the validation period (1965-10-01 – 1970-09-30) that are not NaN	%	
	testing_perc_complete	percentage of observed specific discharge values in the testing period (2001-10-01 – 2020-12-31) that are not NaN	%	
	NSE_lstm	Nash-Sutcliffe model efficiency coefficient of the LSTM in the testing period	–	
	NSE_hbv	Nash-Sutcliffe model efficiency coefficient of the HBV model in the testing period	–	

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