CCAM: China Catchment ~~attributes~~Attributes and ~~meteorology for large sample study in contiguous China~~Meteorology dataset

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Abstract.

The lack of a complied large-scale catchment characteristics dataset is a key obstacle limiting the development of large sample hydrology research in China. We introduce the first large-scale catchment attributes ~~and meteorological time series~~ dataset ~~of contiguous~~in China. ~~To develop the dataset, we~~We compiled diverse data sources ~~to generate basin-oriented features describing the catchment characteristics related to hydrological processes. The proposed dataset consists of catchment characteristics~~, including soil, land cover, climate, topography, and geology, ~~and 29~~to develop the dataset. The dataset also includes catchment scale 31-year meteorological time series ~~(~~from 1990 to ~~2018). The meteorological variables include precipitation, temperature, evapotranspiration, wind speed, ground surface temperature, pressure, humidity and sunshine duration. We also derived a daily potential~~2020 for each basin. Potential evapotranspiration time series based on ~~a modified Penman’s~~Penman's equation~~.~~ is derived for each basin. The ~~studied~~4911 catchments ~~are 4875 catchments within contiguous China derived from digital elevation models. We analysed and organised~~included in the ~~spatial variations of catchment characteristics into a series of maps. Correlation analysis between attributes was conducted. Compared to~~ dataset covers the entire China. We introduced several new indicators describing the catchment geography and the underlying surface compared with previously proposed datasets~~, we derived more catchment characteristics~~. The resulting ~~in~~ dataset has a total of 125 catchment attributes~~, providing a complete description of the catchments. Besides, we propose Normal-Camels-YR, a hydrological~~. The proposed dataset ~~covering~~also includes a separate HydroMLYR dataset containing standardized weekly averaged streamflow for 102 basins ~~of~~in the Yellow River ~~basin with normalized streamflow observations.~~Basin. The standardized streamflow data should be able to support machine learning hydrology research in the Yellow River Basin. The proposed dataset ~~provides numerous opportunities for comparative hydrological research, such as examining the difference in hydrological behaviours across different catchments and building general rainfall-runoff modelling frameworks for many catchments instead of limited to a few. The dataset is~~ is freely available ~~via http://doi.org/10.5281/zenodo.4704017 for community use. We will open-source the complement~~at http://doi.org/10.5281/zenodo.5137288. In addition, the accompanying code for generating the dataset ~~such that the user can generate meteorological series and catchment attributes~~is freely available at https://github.com/haozhen315/CCAM-China-Catchment-Attributes-and-Meteorology-dataset, supporting

the generation of catchment characteristics for any ~~watershed within contiguous China.~~custom basin boundaries. Complied data for the 4911 basins covering the entire China and the open-sourced code should be able to support the study of any arbitrary basins instead of being limited to only a few basins.

1 Introduction

~~Studying a large set of catchments often provides insights that cannot be obtained when looking at a single or few catchments (Coron, Andreassian et al. 2012, Kollat, Reed et al. 2012, Newman, Clark et al. 2015, Lane, Coxon et al. 2019). The hydrologic cycle consists of many sub-processes, including evaporation from the ocean, raindrop~~Rainfall, interception, evaporation and evapotranspiration, groundwater flow, subsurface flow and surface runoff~~, infiltration, etc.~~ are the main components of the terrestrial hydrological cycle. These processes are affected by the nature of the catchment, such as the ability of the soil to hold water. Catchment attributes ~~such as soil characteristics, land cover characteristics and climate indices~~ influence the water movement and storage ~~in these sub-processes~~of the catchment such that hydrologic behaviours can vary across catchments (van Werkhoven, Wagener et al. 2008). ~~The same hydrological model may not be applicable in another basin. However, by examining a large sample of catchments, it is possible for the hydrological model to learn the similarities and differences of hydrological behaviours across catchments. For example, prediction~~Studying a large set of terrestrial catchments often provides insights that cannot be obtained when looking at a single or few (Coron, Andreassian et al. 2012, Kollat, Reed et al. 2012, Newman, Clark et al. 2015, Lane, Coxon et al. 2019). For example, a calibrated model may not be applicable in a watershed with vastly different properties. However, by examining a large sample of catchments, it is possible for a data-driven model to learn the similarities and differences of hydrological behaviours across catchments (Kratzert, Klotz et al. 2019). Prediction in ungauged basins is a challenging problem present in hydrology. The central challenge is how to extrapolate hydrologic information from gauged basins to ungauged ones~~. Solving~~, solving the problem relies on understanding the similarities and differences between different catchments. ~~However, regionally~~Regionally, and temporally imbalanced observations bring a difficulty to the problem. For a ~~hydrologic~~ model to successfully simulate the ungauged areas, it must adapt itself to the different hydrologic behaviours present in different catchments. ~~(Kratzert, Klotz et al. 2019)~~ Kratzert, Klotz et al. (2019) shows encoding catchment characteristics (e.g., soil characteristics, land cover, topography) into a data-driven model can ~~teach~~guide the model to behave differently responding to the meteorological time series input based on different sets of ~~static~~ catchment attributes.

~~(Silberstein 2006, Shen, Laloy et al. 2018, Nevo, Anisimov et al. 2019) pointed out that large~~Large sample hydrological datasets are the foundation and key of many hydrological studies~~.~~ (Silberstein 2006, Shen, Laloy et al. 2018, Nevo, Anisimov et al. 2019). The term big hydrologic data refers to all data influencing the water cycle, such as the meteorological variables, infiltration characteristics of the study area, land use or land cover types, physical and geological features of the study ~~area~~catchment, etc. Many studies ~~cannot be carried out without~~are based on large-scale hydrologic data (Coron, Andreassian et al. 2012, Singh, van Werkhoven et al. 2014, Berghuijs, Aalbers et al. 2017, Gudmundsson, Leonard et al. 2019, Tyralis, Papacharalampous et al. 2019). For hydrological research, basin~~-~~ orientated ~~large sample~~ datasets are of great significance. For example, comparative hydrology (de Araújo and González Piedra 2009, Singh, Archfield et al. 2014) focus on understanding how hydrological processes interact with the ecosystem, in particular, how hydrologic behaviours change under changes in the surface and sub-surface of the earth to determine to what extent hydrological predictions can be transferred from one area to another. Large-sample catchment attributes ~~dataset~~datasets provide opportunities for research studying interrelationships among catchment attributes. ~~(Seybold, Rothman et al. 2017)~~Seybold, Rothman et al. (2017) studied the correlations between river junction angle with geometric factors, downstream concavity, and aridity. ~~(Oudin, Andréassian et al. 2008)~~Oudin, Andréassian et al. (2008) investigates the link between land cover and mean annual streamflow based on 1508 basins representing a large hydroclimatic variety. ~~(Voepel, Ruddell et al. 2011)~~Voepel, Ruddell et al. (2011) examines how the interaction of climate and topography influences vegetation response.

~~Data-driven methods can best benefit from large-scale data. Data-driven approaches have shown great potential in various fields, transforming the applications in many industries (LeCun, Bengio et al. 2015). However, data-driven methods, especially the deep learning-based approaches, usually require high data volumes. Limited data will cause the over-fitting (Blumer, Ehrenfeucht et al. 1987, Abu-Mostafa, Magdon-Ismail et al. 2012) problem. Therefore, big hydrologic data is the fundamental support for the successful deployment of powerful data-driven strategies.~~

~~Traditional hydrological models have some long standing challenges, such as the inability to capture hydrological processes' mechanism complexity (Kollat, Reed et al. 2012), which is due to the structural limitations of the conceptual models. Data-driven methods are proposed to overcome some existing obstacles. Data-driven strategies open a new way for researchers to acquire knowledge transforming the research pattern from hypothesis-driven to data-driven. (Feng, Fang et al. 2020) proposed a flexible data integration fusing various types of observations to improve rainfall-runoff modelling. The research shows that combining different resources of data benefits predictions in regions with high autocorrelation in streamflow. (Wongso, Nateghi et al. 2020) developed a model predicting the state-level, per capita water uses in the United States, taking various geographic, climatic, and socioeconomic variables as input. The research also identified key factors associated with high water usage. (Mei, Maggioni et al. 2020) proposed a statistical framework for spatial downscaling to obtain hyper-resolution precipitation data. The results show improvements compared with the original product. (Brodeur, Herman et al. 2020) applied machine learning techniques, namely bootstrap aggregation and cross validation, to reduce overfitting in reservoir control policy search. (Ni and Benson 2020) proposed an unsupervised machine learning method to differentiate flow regimes and identify capillary heterogeneity trapping, showing the promise of machine learning methods for analysing large datasets from coreflooding experiments. (Legasa and Gutiérrez 2020) propose to apply Bayesian Network for multisite precipitation occurrence generation. The proposed methodology shows improvements for existing methods.~~

World-wide data sharing has become a trend (Wickel, Lehner et al. 2007, Ceola, Arheimer et al. 2015, Blume, van Meerveld et al. 2018, Wang, Chen et al. 2020), and the amounts of hydrologic data available are ever-increasing. However, these data typically came from different providers and are compiled in various formats. ~~For example, ASTGTM[1]~~ASTGTM (Abrams, Crippen et al. 2020) provides a global digital elevation model; GliM (Hartmann and Moosdorf 2012) includes rock types data globally; MODIS provides data products (Knyazikhin 1999, Didan 2015, Myneni, Knyazikhin et al. 2015, Running, Mu et al. 2017, Sulla-Menashe and Friedl 2018) describing features of the land and the atmosphere derived from remote sensing observations; ~~(Yamazaki, Ikeshima et al. 2019)~~Yamazaki, Ikeshima et al. (2019) provides a global flow direction map at three arc-second resolution; HydroBASINS (Lehner 2014) provides basin boundaries at different scales globally; and GDBD (Masutomi, Inui et al. 2009) provides basin boundaries with geographic attributes; GLHYMPS (Gleeson, Moosdorf et al. 2014) provides a global map of subsurface permeability and porosity; SoilGrids250m (Hengl, Mendes de Jesus et al. 2017) dataset provides global numeric soil properties. Local government agencies often hold meteorological data such as precipitation and evaporation, and the amount of this data is also growing~~, however, data transparency has still been a problem (Viglione, Borga et al. 2010). The~~.

However, the data mentioned above are rarely spatially aggregated to the catchment~~-~~ scale, making it difficult for researchers to use these data. Properly pre-processed and formatted datasets ~~on a large scale~~ are of great importance for ~~the~~ hydrology research. Searching for appropriate data sources, pre-processing, and formatting often consumes a lot of ~~researchers'~~ time. In some cases, individual research groups either do not know where to obtain the appropriate data or cannot properly process the data to receive the desired format. In summary, although data sharing is being advocated in the community, it is usually difficult for the public to obtain the required data, either because there are not enough observations or because of the difficulties in the data processing.

~~In summary, both data-driven and traditional hydrological research need diverse hydrologic datasets to learn the generalisation capability from one area to another. For a model to adapt to various behaviours in different catchments, the dataset must be large enough to represent the complex heterogeneity presented in the natural hydrologic system. Although data sharing is being advocated in the community, it is usually difficult for the public to obtain certain data such as meteorological data and streamflow observations, either because there are not enough observations or because there are no open access permissions.~~

Recently, there are efforts (Addor, Newman et al. 2017, Alvarez-Garreton, Mendoza et al. 2018, Chagas, Chaffe et al. 2020, Coxon, Addor et al. 2020)~~ compiling different types of data sources to form large-scale hydrological datasets. These four collected datasets cover the continental United States, Chile, Brazil, and Great Britain. (Addor, Do et al. 2020) reviewed these datasets and discussed the guidelines for producing large-sample hydrological datasets and the limitations of the currently proposed datasets. The CAMELS dataset has been used to support a lot of research. Based on CAMELS, (Kratzert, Klotz et~~

~~[1] https://asterweb.jpl.nasa.gov/gdem.asp~~

~~al. 2018) built a Long Short-Term Memory (LSTM) network for rainfall-runoff modelling, showing that one model can predict the discharge for a variety of catchments. (Knoben, Freer et al. 2019) compared metrics used in hydrology based on simulations on many basins. (Tyralis, Papacharalampous et al. 2019) studied the relationship between the shape parameter and basin attributes based on the sizeable basin-oriented dataset.~~

~~However, there is no large-scale compilation of hydrological datasets in contiguous China. An alternative is on a global scale, the HydroATLAS (Linke, Lehner et al. 2019) dataset. However, since it is on a world-wide scale, compared with other datasets constructed for regions, the dataset lacks many attributes and is not built according to the CAMELS standards. Besides, the climatic data is not up to date (1950-2000), and the derivation of climatic data lacks ground surface observations inputs, such that the data quality is not guaranteed.~~

~~Therefore, researchers still need to do repetitive works to compile data from different sources such as obtaining historical meteorological data (temperature, rainfall, evapotranspiration) of a catchment in contiguous China. Inspired by (Addor, Newman et al. 2017), in this paper, we present a catchment scale hydrologic dataset compiling a wide variety of hydrological data, including basin topography, climate indices, land cover characteristics, soil characteristics and geological characteristics covering contiguous China.~~

to compile different types of data sources forming large scale hydrological datasets. These four collected datasets cover the continental United States, Chile, Brazil, and Great Britain. Addor, Do et al. (2020) reviewed these datasets and discussed the guidelines for producing large-sample hydrological datasets and the limitations of the currently proposed datasets. The static properties of 671 river basins in the United States are calculated by CAMELS (Addor, Newman et al. 2017), which is an extension of a previously proposed hydrometeorological data set (Newman, Clark et al. 2015). Unfortunately, it is impossible to publish streamflow data in China for the time being. The CAMELS dataset has been used to support a lot of research. For example, Knoben, Freer et al. (2019) compared metrics used in hydrology based on simulations on many basins. Tyralis, Papacharalampous et al. (2019) studied the relationship between the shape parameter and basin attributes based on the sizeable basin-oriented dataset.

There is currently no compilation of China-specific catchment attributes datasets. An alternative, the HydroATLAS (Linke, Lehner et al. 2019) dataset, which is on a global scale, is basically performing zonal statistics on the source data. HydroATLAS lacks many indicators which need derivations based on the source data, such as rainfall seasonality, the fraction of precipitation falling as snow, basin shape factors and root depth distributions. What's worse, the meteorological data is only up to 2000, which is outdated.

In summary, a lack of a complied catchment attributes dataset is a key obstacle limiting the development of large sample hydrology research in China. Inspired by (Addor, Newman et al. 2017), we complied multiple data sources, including basin topography, climate indices, land cover characteristics, soil characteristics and geological characteristics. Different from

(Addor, Newman et al. 2017), the catchments included in the dataset covers the entire study area, instead of being limited to a few.

The proposed dataset is the first dataset providing catchments meteorological time series and catchments attributes of ~~contiguous~~ China. We compiled and named the dataset following most standards of the previously proposed datasets. ~~Unlike CAMELS and CAMELS-CL, catchments in the proposed dataset are not selective. Instead, the~~The dataset consists of all ~~generated basins~~derived basin boundaries from the Digital Elevation Model (DEM~~), based on~~) which came from the Global Drainage Basin Dataset (Masutomi, Inui et al. 2009). The Global Drainage Basin Dataset (GDBD) is derived at high-resolution (100m-1km) and has a good geographic agreement with existing global drainage basin data in China~~[2]. Besides, an essential feature of the~~. In addition, previously proposed ~~dataset is that it provides a complete description of the catchment, rather than an abstraction. For example, both CAMELS and CAMELS-CL only~~ datasets (Addor, Newman et al. 2017, Alvarez-Garreton, Mendoza et al. 2018, Chagas, Chaffe et al. 2020, Coxon, Addor et al. 2020) report only the most frequent ~~and second most frequent~~ catchment land cover and lithology types. Instead, ~~the proposed dataset~~CCAM calculates the ~~proportion~~proportions of ~~each~~all land cover and lithology ~~type for each catchment to serve data-driven research better. We also introduced many more climate characteristics and soil characteristics to support more diverse potential research~~types.

~~Researchers from different places can use the proposed dataset in conjunction with their streamflow data, simplifying organising and compiling various data resources, which is usually repetitive work. The proposed dataset is undoubtedly the most comprehensive catchment attributes and meteorological time series dataset in contiguous China and is suitable for multi-purpose data-driven research. The dataset consists of basin boundaries in the shapefile format, computed catchment attributes of climate, land cover, soil, topography and lithology and 29-year meteorological time series. Table 1 compares the number of static attributes between CAMELS, CAMELS-BR, and the proposed dataset.~~

In addition to the basin-wise attributes provided in CCAM, we propose HydroMLYR, a hydrology dataset for machine learning research in the Yellow River Basin providing weekly averaged standardized streamflow data for 102 basins in the Yellow River Basin (YRB). HydroMLYR is proposed to support machine learning hydrology research at YRB. Traditional hydrological models have some long standing challenges, such as the inability to capture hydrological processes' mechanism complexity (Kollat, Reed et al. 2012), which is due to the structural limitations of the conceptual models. Data-driven strategies represented by machine learning are proposed to overcome some existing obstacles and they open a new way for researchers to acquire knowledge transforming the research pattern from hypothesis-driven to data-driven. Feng, Fang et al. (2020)

~~[2] In this study, gauge streamflow measurements are not available in areas other than the Yellow River such that it is infeasible to specify a gauge location for generating the basin boundary for most of the areas. Streamflow measurements have strict redistribution policy; however, local research institutions have their streamflow measurements for hydrological research, the proposed dataset can used in conjunction with the streamflow data of researchers in various places.~~

proposed a flexible data integration fusing various types of observations to improve rainfall-runoff modelling. The research shows that combining different resources of data benefits predictions in regions with high autocorrelation in streamflow. Wongso, Nateghi et al. (2020) developed a model predicting the state-level, per capita water uses in the United States, taking various geographic, climatic, and socioeconomic variables as input. The research also identified key factors associated with high water usage. Mei, Maggioni et al. (2020) proposed a statistical framework for spatial downscaling to obtain hyper-resolution precipitation data. The results show improvements compared with the original product. Brodeur, Herman et al. (2020) applied machine learning techniques, namely bootstrap aggregation and cross-validation, to reduce overfitting in reservoir control policy search. Ni and Benson (2020) proposed an unsupervised machine learning method to differentiate flow regimes and identify capillary heterogeneity trapping, showing the promise of machine learning methods for analysing large datasets from coreflooding experiments. Legasa and Gutiérrez (2020) propose to apply Bayesian Network for multisite precipitation occurrence generation, and the proposed methodology shows improvements for existing methods. The proposed data set can be used to develop or verify machine learning models in the YRB.

The paper is organized as follows: Section 2 describes the study area. Section 3-7 describes the five classes of the computed catchment attributes. ~~In section 3-7, each unit follows the same structure: first introduce the meaning and significance of each added feature and data source used, then describe the variables' spatial variability if necessary.~~ Section 8 describes the proposed catchment~~-~~ scale meteorological ~~forcing~~ time series. Section 9 introduce the ~~Normal-Camels-YR~~HydroMLYR dataset~~, which provides normalized streamflow measurements for 102 catchments of Yellow River.~~. Section 10 describes the code and data availability. Section 11 ~~presents~~is the concluding remark.

~~In summary, our contributions are as follows:~~

~~(1) The proposed dataset is the first large-scale dataset containing catchment-scale meteorological time series of contiguous China, which is the basis for many hydrological studies.~~

~~(2) We present the first basin-oriented static attributes dataset in contiguous China.~~

~~(3) We introduce several new catchment characteristics providing a complete description of the catchment compared with the previously proposed datasets such that the proposed dataset is prepared for potential hydrological studies.~~

~~(4) We offer a self-contained dataset covering 102 basins of the Yellow River basin with normalized runoff observation supporting many potential studies.~~

~~(5) We will open-source the code for generating the dataset such that the user can generate a dataset for any watershed within contiguous China.~~

~~**Table 1 Number of computed attributes in CAMELS, CAMELS-BR and the proposed dataset.**~~

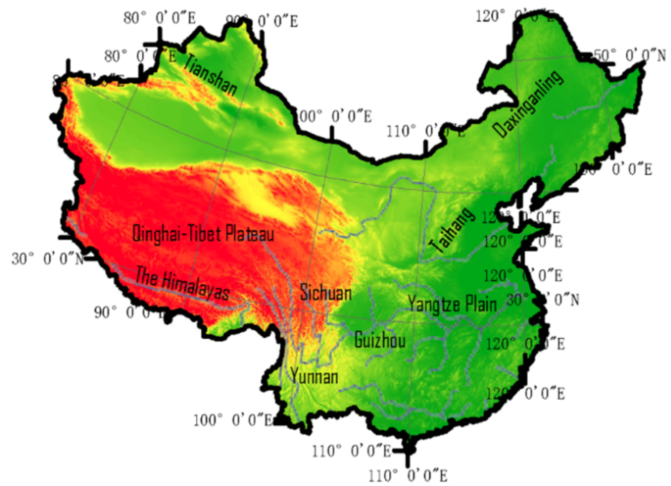
~~Attribute class~~	~~CAMELS(A17)~~	~~CAMELS-BR~~	~~Ours~~
~~Location and topography~~	~~9~~	~~11~~	~~12~~

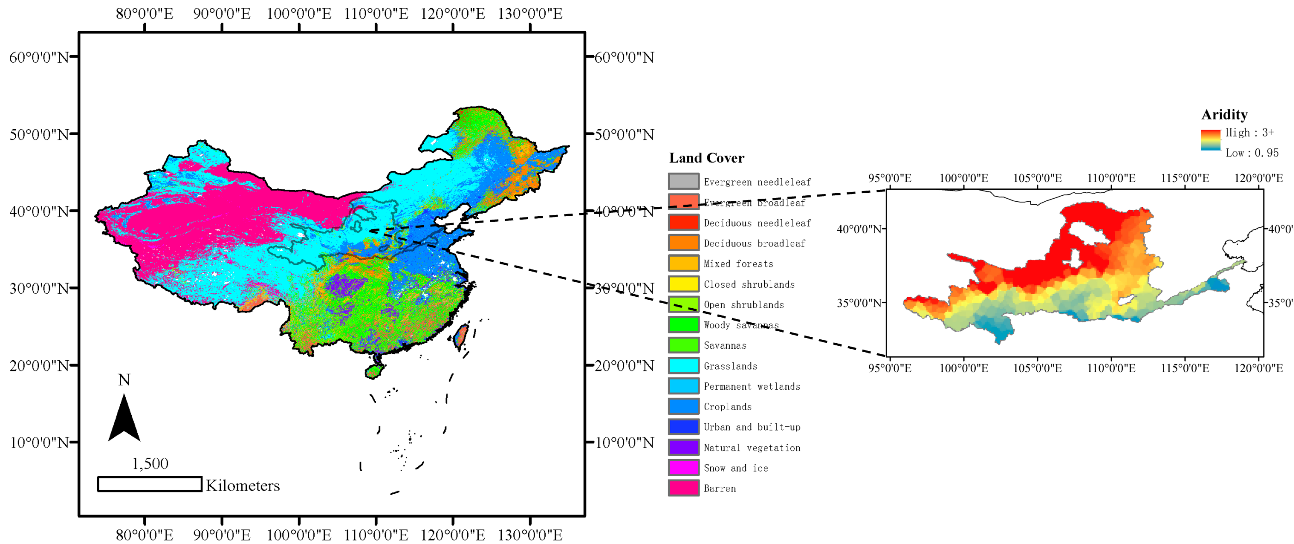
~~Geology~~	~~7~~	~~7~~	~~18~~
~~Soil~~	~~11~~	~~6~~	~~54~~
~~Land cover~~	~~8~~	~~11~~	~~22~~
~~Climatic indices~~	~~11~~	~~13~~	~~17~~
~~Human intervention indices~~	~~not computed~~	~~4~~	~~2~~
~~Total~~	~~46~~	~~52~~	~~125~~

~~**Table 2 Summary of basin daily discharge and forcing data in CAMELS, CAMELS-BR and the proposed dataset.**~~

~~Forcing data class~~	~~CAMELS~~		~~CAMELS-BR~~	~~Ours~~
~~Temperature~~	~~available~~	~~available~~	~~available~~	
~~Precipitation~~	~~available~~	~~available~~	~~available~~	
~~Solar radiation~~	~~available~~	~~**not available**~~	~~available~~	
~~Day length~~	~~available~~	~~**not available**~~	~~**not available**~~	
~~Sunshine hours~~	~~**not available**~~	~~**not available**~~	~~available~~	
~~Humidity~~	~~available~~	~~**not available**~~	~~available~~	
~~Snow water equivalent~~	~~available~~	~~**not available**~~	~~**not available**~~	
~~Wind velocity~~	~~**not available**~~	~~**not available**~~	~~available~~	
~~Ground surface pressure~~	~~available~~	~~**not available**~~	~~available~~	
~~Observed evaporation~~	~~**not available**~~	~~available~~	~~available~~	
~~Potential evapotranspiration~~	~~**not available**~~	~~available~~	~~available~~	
~~Streamflow~~	~~available~~		~~available~~	~~partially available (see Section 9)~~

2 Study area





~~(a)~~

~~(b)~~

Figure 1~~. Overview of the study area. The study area covers a wide range of latitude and longitude, from 18.2° N to 52.3° N, and from 76.0° E to 134.3° E. (a) The main geographical features map of contiguous China. China is mountainous; mountains and hills occupy two-thirds of the area. (b) The distribution map of the delimited catchments based on the ASTER DEM, the catchments studied are all catchment areas delimited from the DEM, covering contiguous China, with 4875 catchments, most of which are 2000 to 5000 square kilometres.~~

: Left: Study area of CCAM and the distribution of land cover types. The studied basins cover the whole of China. Right: Study area of HydroMLYR and the distribution of aridity (PET/P) index. YRB is a generally arid area. The data set provided can be used as a good sample for studying hydrology in arid regions.

The study area corresponds to ~~contiguous~~the whole of China~~,~~ (Fig. 1), with diverse climate and terrain characteristics, spanning from 18.2° N to 52.3° N and 76.0° E to 134.3° E. Mountains, plateaus, and hills account for about two-thirds of areas of ~~contiguous~~ China, and the remaining are basins and plains. China's topography is like a three-level ladder, high in the west and low in the east. The Qinghai-Tibet Plateau, the highest plateau globally, located in the west of ~~contiguous~~ China, with a mean elevation of over 4000 meters, is the first step of China's topography. The Xinjiang region, the Loess Plateau, the Sichuan Basin, and the Yunnan-Guizhou Plateau to the north and east are the second step of China's topography. The mean sea level here is between 1000 to 2000 meters. Plains and hills dominate the east of the Daxinganling-Taihang Mountain to the coastline, the third step of ~~contiguous~~ China. The elevation of this step descends to 500-1,000 meters. To better characterize the studied catchments, we have derived various attributes. Table 1 compares the number of derived attributes between several proposed datasets.

Table 1: Number of computed attributes in CAMELS, CAMELS-BR and CCAM.

Attribute class	CAMELS(A17)	CAMELS-BR	CCAM
Location and topography	9	11	12
Geology	7	7	18
Soil	11	6	54
Land cover	8	11	22
Climatic indices	11	13	17
Human intervention indices	not computed	4	2
Total	46	52	125

In ~~contiguous~~ China, precipitation and temperature vary significantly in different places, forming a diverse climate environment. According to the Köppen Climate Classification System, from northwest to southeast, China's climate gradually evolves from Cold desert (BW_k) climate, Tundra (ET) climate, Warm and temperate continental (D_{fa} and D_{wb}) climate to Humid subtropical (C_{wa}) climate and Warm oceanic (C_{fa}) climate. From the perspective of temperature zones, there are tropical, subtropical, warm temperate, medium temperate, cold temperate and Qinghai-Tibet Plateau regions, and there are humid regions, semi-humid regions, semiarid regions, and arid regions from the perspective of wet and dry zones. Moreover, the same temperature zone can contain different dry and wet zones. Therefore, there will be differences in heat and wetness in the same climate type. The complexity of the terrain makes the climate even more complex and diverse. Besides, China has a wide range of regions affected by the alternating winter and summer monsoons. Compared with other parts of the world at the same latitude, these areas have low winter temperatures, high summer temperatures, significant annual temperature differences, and concentrated precipitation in summer. The cold and dry winter monsoon occurs in Asia's interior, far away from the ocean. Under its influence, winter rainfall in most parts of China is low, accompanied by low temperature. The summer monsoon is warm and humid, coming from the Pacific Ocean and the Indian Ocean. Under its influence, precipitation generally increases. Table 2 compares the provided forcing variables in CAMELS, CAMELS-BR and CCAM.

Table 2: Summary of forcing variables provided in CAMELS, CAMELS-BR and CCAM.

Forcing data class	CAMELS	CAMELS-BR	CCAM
Temperature	available	available	available
Precipitation	available	available	available
Solar radiation	available	**not available**	available
Day length	available	**not available**	**not available**
Sunshine hours	**not available**	**not available**	available
Humidity	available	**not available**	available
Snow water equivalent	available	**not available**	**not available**
Wind velocity	**not available**	**not available**	available
Ground surface pressure	available	**not available**	available
Observed evaporation	**not available**	available	available
Potential evapotranspiration	**not available**	available	available

Table 3: Summary table of catchment attributes available in the proposed dataset.

Attribute class	Attribute name	Description	Unit	Data source
Climate indices (computed for 1 Oct 1990 to 30 Sep 2018)	pet_mean	mean daily pet (Penman–Monteith equation)	mm d^{-1}	(Subramanya 2013)
	evp_mean	mean daily evaporation (observations)	mm d^{-1}	SURF_CLI_CHN_MUL_DAY3F[3]
	gst_mean	mean daily ground surface temperature	°C	
	pre_mean	mean daily precipitation	mm d^{-1}	
	prs_mean	mean daily ground surface pressure	hPa	
	rhu_mean	mean daily relative humidity	-	
	ssd_mean	mean daily sunshine duration	h	

[3] http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_DAY.html

tem_mean	mean daily temperature	°C
win_mean	mean daily wind speed	m s^{-1}
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], values close to 0 indicate uniform precipitation throughout the year)	-
high_prec_freq	frequency of high-precipitation days (⩾ 5 times mean daily precipitation)	d yr^{-1}
high_prec_dur	average 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 (⩾ 5 times mean daily precipitation) occur	season
low_prec_freq	frequency of dry days (< 1mm d^{-1})	d yr^{-1}
low_prec_dur	average duration of dry periods (number of consecutive days < 1 mm d^{-1})	d
low_prec_timing	season during which most dry days (< 1 mm d^{-1}) occur	season
frac_snow_daily	fraction of precipitation falling as snow (for days colder than 0 °C)	-
p_seasonality	seasonality and timing of precipitation, positive [negative] values indicate that precipitation peaks in summer [winter], values	-

		close to 0 indicate uniform precipitation throughout the year		
Geological characteristics	geol_porosity	subsurface porosity	-	(Gleeson, Moosdorf et al. 2014)
	geol_permeability	subsurface permeability (log-10)	m^2	
	ig	fraction of the catchment area associated with ice and glaciers	-	(Hartmann and Moosdorf 2012)
	pa	fraction of the catchment area associated with acid plutonic rocks	-	
	sc	fraction of the catchment area associated with carbonate sedimentary rocks	-	
	su	fraction of the catchment area associated with unconsolidated sediments	-	
	sm	fraction of the catchment area associated with mixed sedimentary rocks	-	
	vi	fraction of the catchment area associated with intermediate volcanic rocks	-	
	mt	fraction of the catchment area associated with metamorphic	-	
	ss	fraction of the catchment area associated with siliciclastic sedimentary rocks	-	
	pi	fraction of the catchment area associated with intermediate plutonic rocks	-	
	va	fraction of the catchment area associated with acid volcanic rocks	-	
	wb	fraction of the catchment area associated with water bodies	-	

	pb	fraction of the catchment area associated with basic plutonic rocks	-	
	vb	fraction of the catchment area associated with basic volcanic rocks	-	
	nd	fraction of the catchment area associated with no data	-	
	py	fraction of the catchment area associated with pyroclastic	-	
	ev	fraction of the catchment area associated with evaporites	-	
Land cover characteristics	lai_max	maximum monthly mean of the leaf area index (based on 12 monthly means)	-	(Myneni, Knyazikhin et al. 2015)
	lai_diff	difference between the maximum and minimum monthly mean of the leaf area index (based on 12 monthly means)	-	
	ndvi_mean	mean normalized difference vegetation index (NDVI)	-	(Didan 2015)
	root_depth_50	root depth (percentiles=50% extracted from a root depth distribution based on IGBP land cover)	m	Eq. 2 and Table 2 in (Zeng 2001)
	root_depth_99	root depth (percentiles=99% extracted from a root depth distribution based on IGBP land cover)	m	
	evergreen needleleaf tree	catchment area fraction covered by evergreen needleleaf tree	-	(Sulla-Menashe and Friedl 2018)
	evergreen broadleaf tree	catchment area fraction covered by evergreen broadleaf tree	-	

	deciduous needleleaf tree	catchment area fraction covered by deciduous needleleaf forests	-	
	deciduous broadleaf tree	catchment area fraction covered by deciduous broadleaf tree	-	
	mixed forest	catchment area fraction covered by mixed forest	-	
	closed shrubland	catchment area fraction covered by closed shrubland	-	
	open shrubland	catchment area fraction covered by open shrubland	-	
	woody savanna	catchment area fraction covered by woody savanna	-	
	savanna	catchment area fraction covered by savanna	-	
	grassland	catchment area fraction covered by grassland	-	
	permanent wetland	catchment area fraction covered by permanent wetland	-	
	cropland	catchment area fraction covered by cropland	-	
	urban and built-up land	catchment area fraction covered by urban and built-up land	-	
	cropland/natural vegetation	catchment area fraction covered by cropland/natural vegetation	-	
	snow and ice	catchment area fraction covered by snow and ice	-	
	barren	catchment area fraction covered by barren	-	
	water bodies	catchment area fraction covered by water bodies	-	
Topography, location~~,~~ and	basin_id	drainage basin identifiers	-	(Masutomi, Inui et al. 2009)
	pop	population	people	

Human intervention	pop_dnsty	population density	people km^{-2}	
	lat	mean latitude	°N	
	lon	mean longitude	°E	
	elev	mean elevation	M	
	area	catchment area	km^{2}	
	slope	mean slope	m km^{-1}	(Horn 1981)
	length	The length of the mainstream measured from the basin outlet to the remotest point on the basin boundary. The mainstream is identified by starting from the basin outlet and moving up the catchment.	~~km~~Km	(Subramanya 2013)
	form factor	catchment area / (catchment length)^{2}	-	
	shape factor	(catchment length)^{2} / catchment area	-	
	compactness coefficient	perimeter of the catchment / perimeter of the circle whose area is that of the basin	-	
	circulatory ratio	catchment area / area of circle of catchment perimeter	-	
	elongation ratio	diameter of circle whose area is basin area / catchment length	-	
Soil	pdep	soil profile depth	cm	(Shangguan, Dai et al. 2013)
	clay	percentage of clay content of the soil material	%	
	sand	percentage of sand content of the soil material	%	
	por	porosity	cm^{3} cm^{-3}	

	silt	percentage of silt content of the soil material	%	
	grav	rock fragment content	%	
	som	soil organic carbon content	%	
	log_k_s4F[4]	log-10 transformation of saturated hydraulic conductivity	cm d^{-1}	(Dai, Xin et al. 2019)
	theta_s[4]	saturated water content	cm^3 cm^{-3}	
	tksatu[4]	thermal conductivity of unfrozen saturated soils	W m^{-1} K^{-1}	
	bldfie[4]	bulk density	kg m^{-3}	(Hengl, Mendes de Jesus et al. 2017)
	cecsol[4]	cation-exchange capacity	cmol+ kg^{-1}	
	orcdrc[4]	organic carbon content	g kg^{-1}	
	phihox[4]	pH in H2O	10^{-1}	
	bdticm	depth to bedrock	cm	

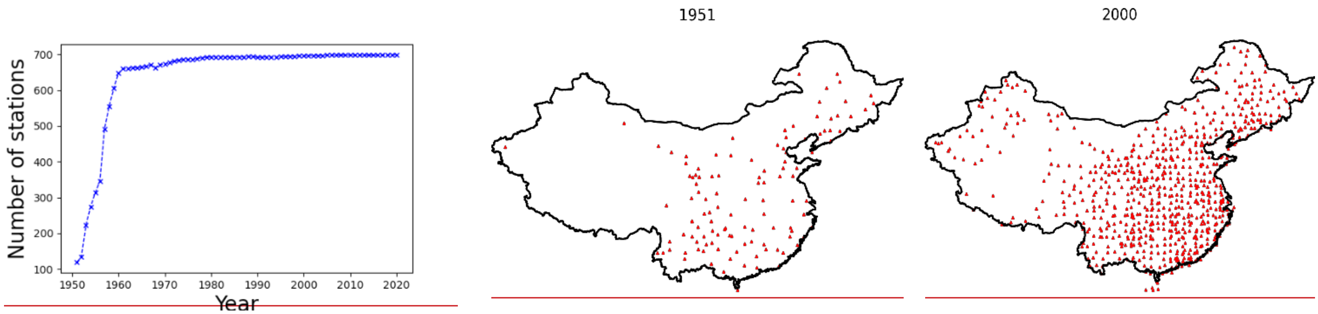
3 ~~Climate~~Climatic indices

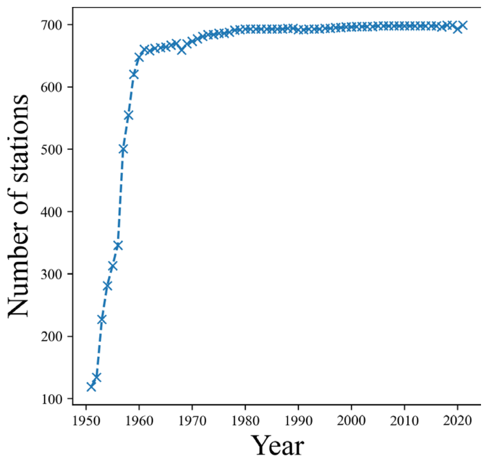
~~Meteorological raw~~ Raw meteorological data ~~was~~is provided by the China Meteorological Data ~~Network[3]~~Network, released as the SURF_CLI_CHN_MUL_DAY (V3.0) dataset[5], which provides ~~complete variable types and~~ the longest period (1951-~~2018~~2020) of meteorological time series ~~of~~in China. The SURF_CLI_CHN_MUL_DAY product includes site observations of pressure, temperature, relative humidity, precipitation, evaporation, wind speed, sunshine duration, and ground surface temperature~~. The summary is presented in Table 4.~~ (Table 4). The Inverse distance weighting method is used for interpolating the site observations. ~~Climate indices are then obtained by taking the average of the catchment-scale extraction from the interpolated raster.~~ To ensure data quality, we ~~chose~~use the latter ~~29~~31-year record (from 1990 to ~~2018~~2020) to construct the dataset since sites' distribution was sparse in the early days (Fig. 2). We computed more climatic characteristics compared with other datasets (Table 2). These ~~characteristics have critical potential effects on the~~variables are useful in hydrological ~~processes~~modelling; for example, wind speed can affect actual evapotranspiration. To be consistent with the CAMELS (Addor, Newman et al. 2017), we ~~also~~ determined all climatic attributes (Woods 2009) provided in the CAMELS dataset. ~~The~~As a

[4] The data source contains multi-layer soil data, soil characteristics for all layers are determined.

[5] SURF_CLI_CHN_MUL_DAY is freely available for global researchers.

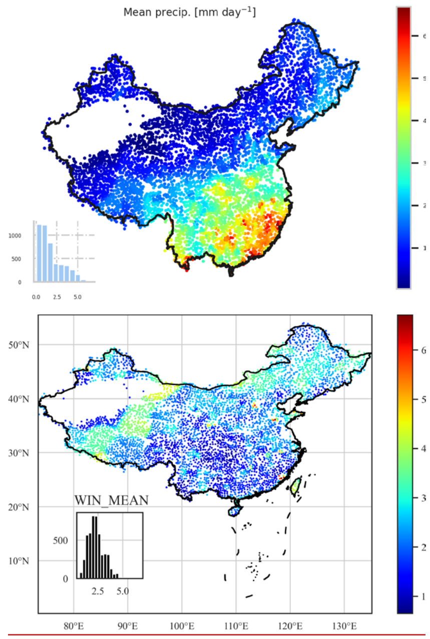
result, the proposed dataset provides more meteorological variables and longer time series (1990-~~2018~~2020) than CAMELS and CAMELS-CL. A summary of the ~~computed Climate~~derived climate indices is presented in Table 3. The national ~~distribution~~distributions of ~~meteorological attributes of catchments is~~the climate indicators are shown in ~~Fig. 3.~~Fig. 3.



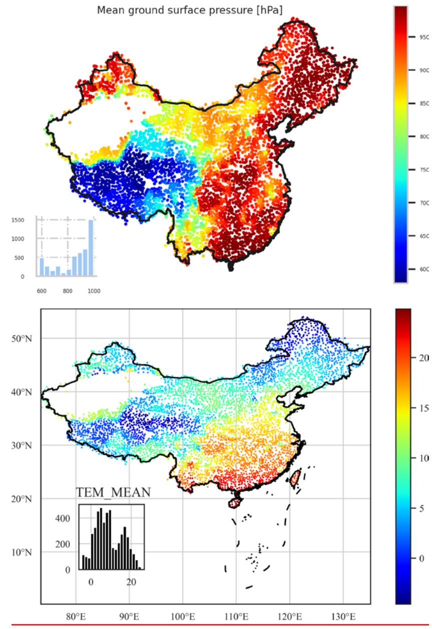


~~(a)~~ ~~(b)~~ ~~(c)~~

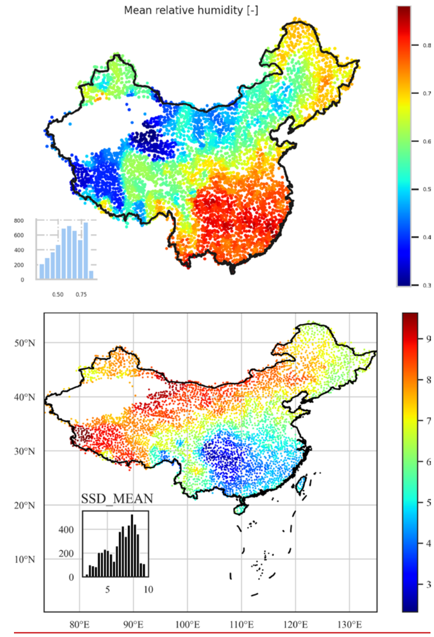
Figure 2~~. Overview of changes~~: Changes in the number ~~and distribution~~ of meteorological stations in China. ~~(a) The number of meteorological stations varies with the year.~~ There were only 119 stations in 1951. This number increased rapidly from 1951 to the early 1960s, and the number of stations remained stable after 2000. ~~(b) Distribution map of China's meteorological stations in 1951. (c) Distribution map of China's meteorological stations in 2000~~To ensure the data quality, we used the latter 31-year records (from 1990 to 2020) to construct the dataset.


Mean precip. [mm day^{-1}]
WIN_MEAN

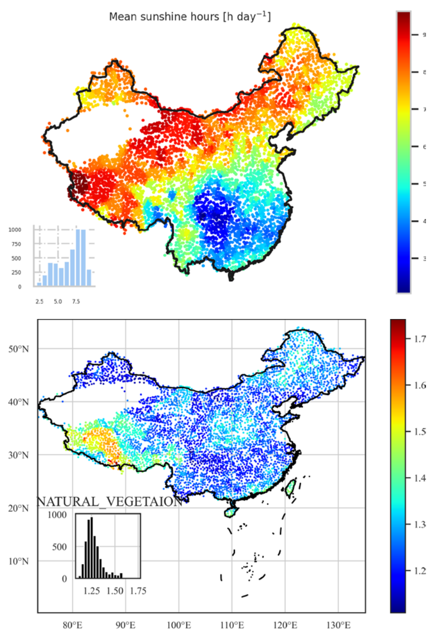
(a)


Mean ground surface pressure [hPa]
TEM_MEAN

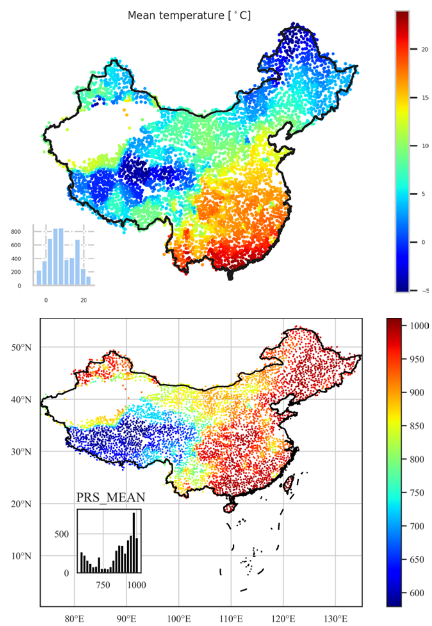
(b)


Mean relative humidity [-]
SSD_MEAN

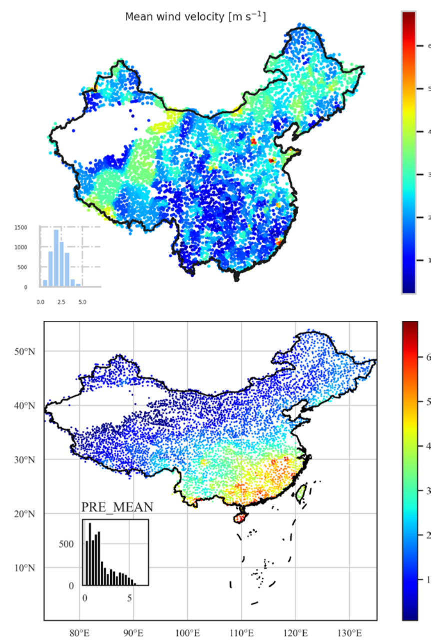
~~(c)~~I


Mean sunshine hours [h day^{-1}]
NATURAL_VEGETAION

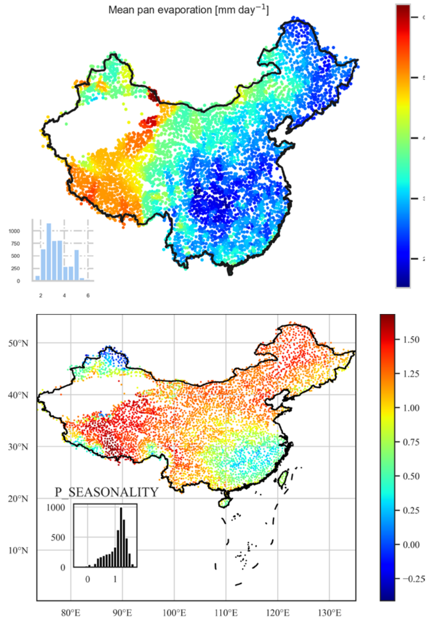
(d)


Mean temperature [$^\circ$C]
PRS_MEAN

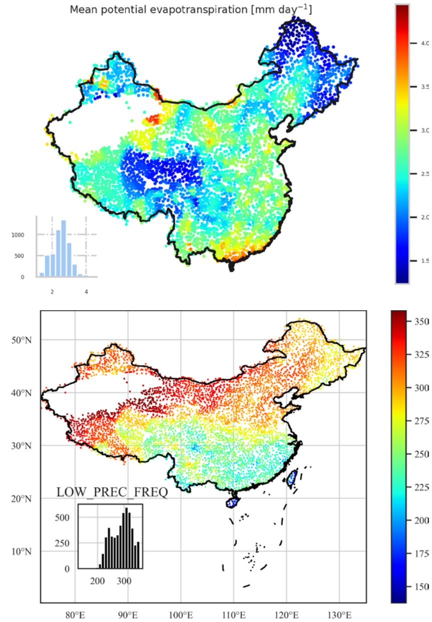
~~(e)~~I


Mean wind velocity [m s^{-1}]
PRE_MEAN

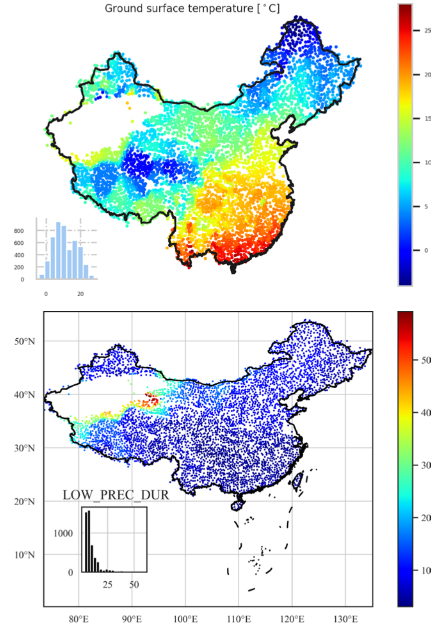
(f)


Mean pan evaporation [mm day^{-1}]
P_SEASONALITY

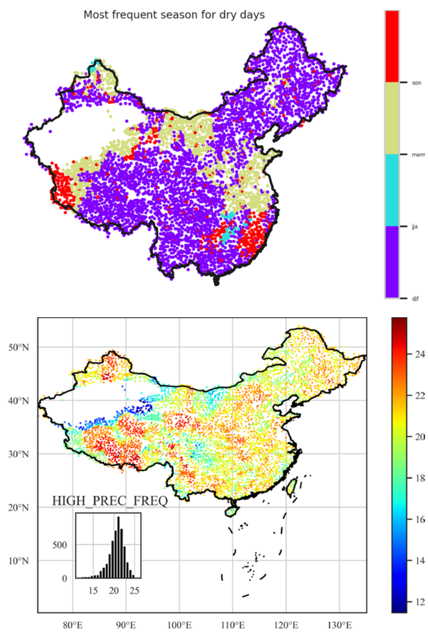
(g)


Mean potential evapotranspiration [mm day^{-1}]
LOW_PREC_FREQ

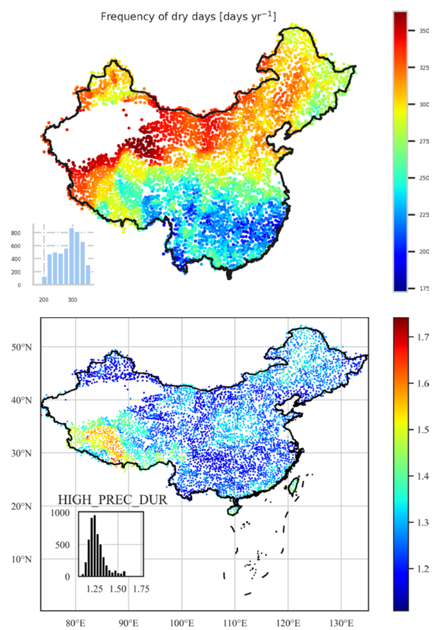
(h)


Ground surface temperature [$^\circ$C]
LOW_PREC_DUR

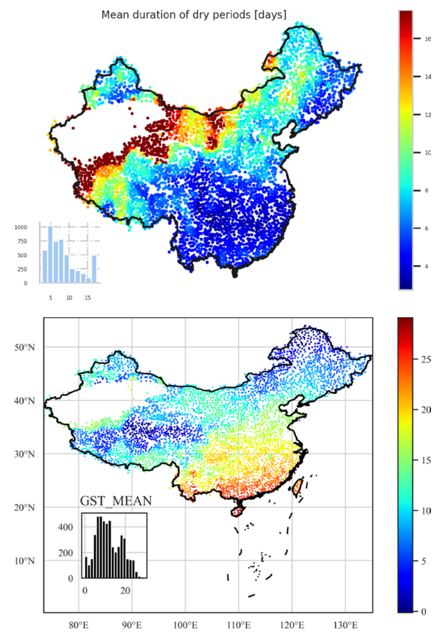
(i)


Most frequent season for dry days
HIGH_PREC_FREQ

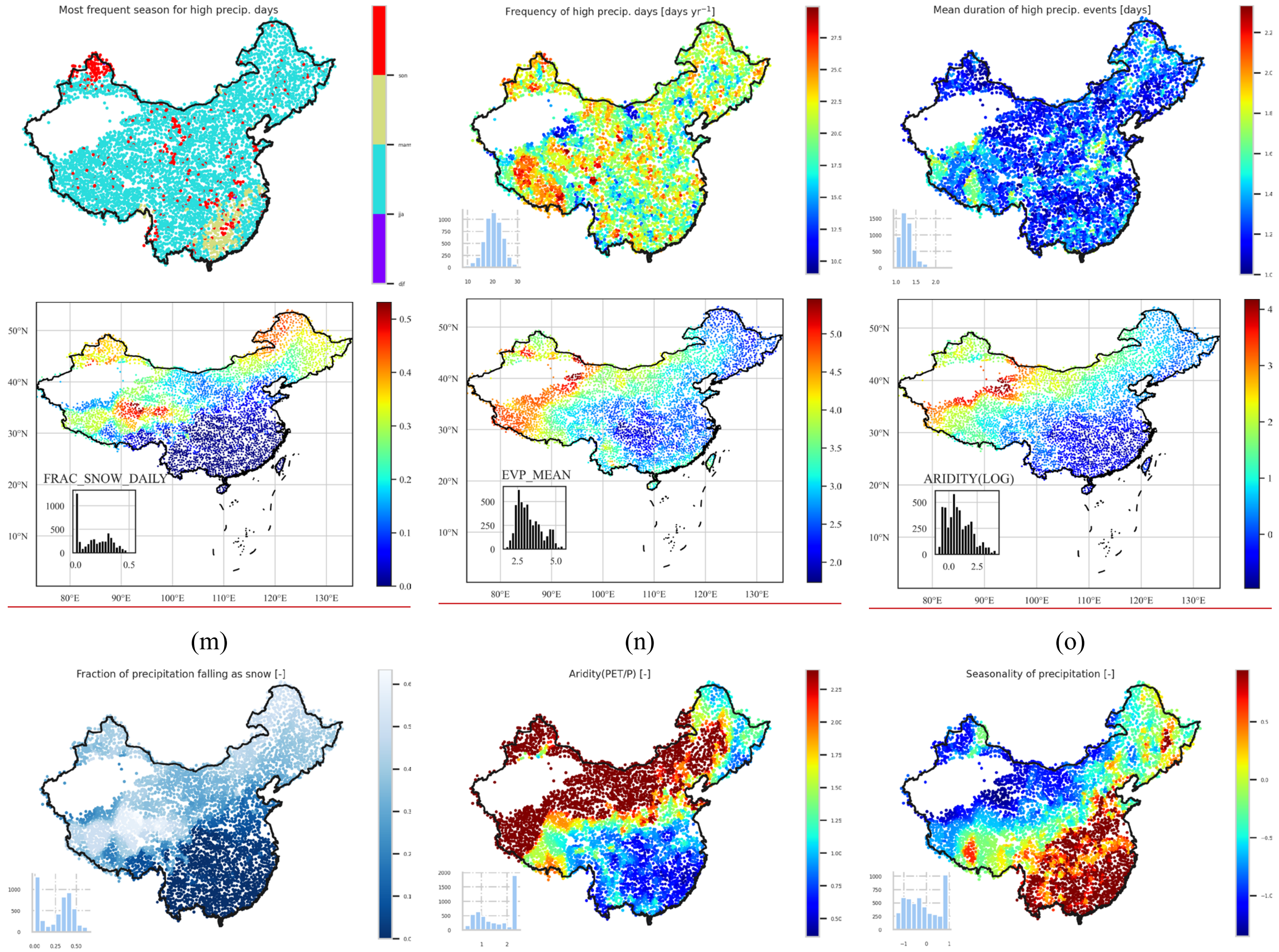
(j)


Frequency of dry days [days yr^{-1}]
HIGH_PREC_DUR

(k)


Mean duration of dry periods [days]
GST_MEAN

(l)



~~(p)~~ ~~(q)~~ ~~(r)~~

Figure 3~~. Maps~~: Distributions of climatic indices over ~~contiguous~~ China. ~~The histograms and bar plots indicate~~ All basins are plotted in the ~~number~~same size. When extreme values of ~~catchments (out of 4875) in each bin or category~~a variable affect visualization (cause most areas to have the same colour), the log values are used for visualization.

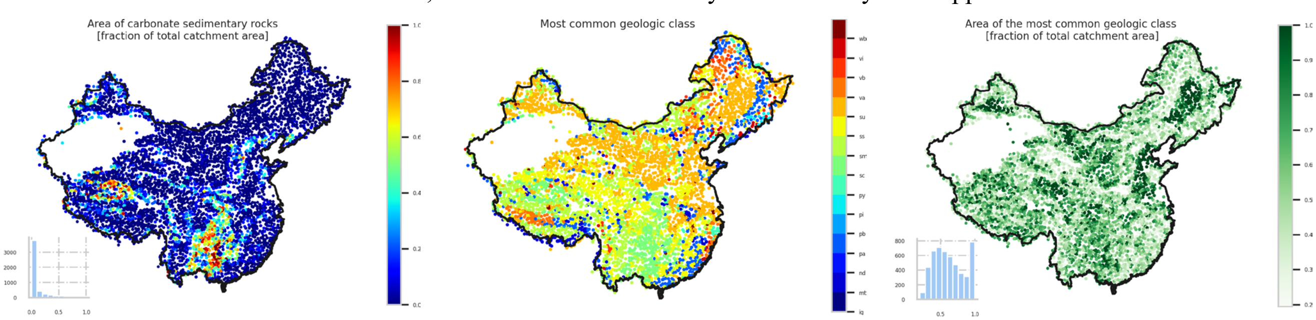
The instruments for measuring potential evaporation were updated from 2000 to 2005. Early observations can be multiplied by a correction coefficient to approximate the new tools. However, the coefficient varies across stations making the approach infeasible. To complement this, we calculated potential evapotranspiration (PET) based on a modified Penman's Equation (~~see~~ Appendix A) and other observed meteorological variables, providing a series of consistent ~~evapotranspiration estimation~~potential evaporation estimations for reference.

The average daily precipitation in ~~contiguous~~ China is highest in the southeast and lowest in the northwest. It is also higher in the coastal areas than in the interior land. Ground surface pressure is positively correlated with elevation, the highest in the Qinghai-Tibet Plateau and the lowest in the Southeast Plain. The average relative humidity is generally positively correlated with precipitation; they are also higher in some forested areas, such as the Taihang Mountains and Daxingan Mountains. The Qinghai-Tibet Plateau has the lowest average temperature, and the southern coastal area has the highest. A distinctive feature of the distribution of wind speed is the high wind speed in mountainous areas. The highest wind speed occurs in the southeast coastal area (> 6 meters per second). ~~Refer to Section 8 for a detailed description of the proposed catchment-scale meteorological time series dataset of contiguous China.~~

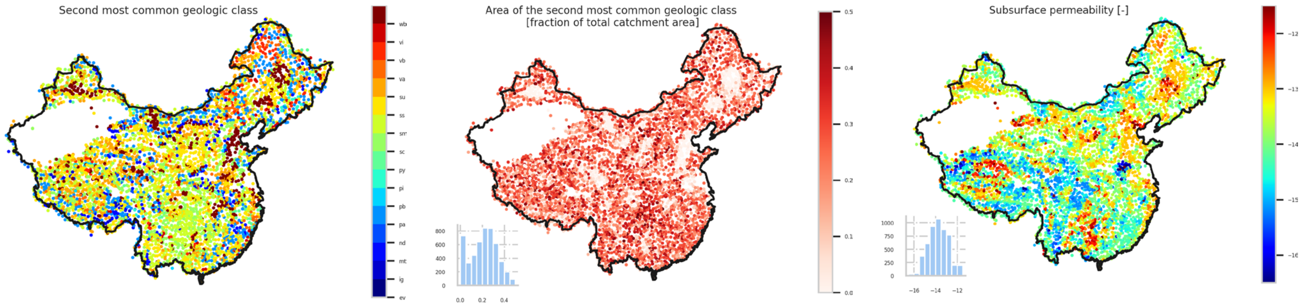
4 Geology

To describe the lithological characteristics of each catchment, we used the same two global datasets as CAMELS, Global Lithological Map (~~GLiM~~GliM) (Hartmann and Moosdorf 2012) and ~~GLobal HYdrogeology~~Global Hydrogeology MaPS (GLHYMPS) (Gleeson, Moosdorf et al. 2014). Figure 4 presents the ~~results~~distributions of the geological types.

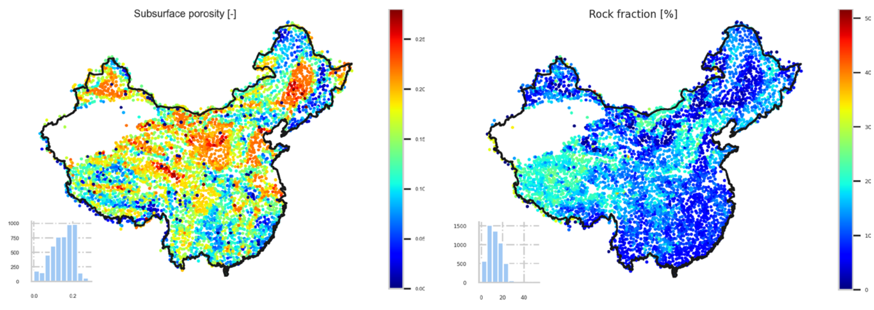
GLiM provides a high resolution global lithological map assembled from existing regional geological maps; it has been widely used for constructing datasets (e.g. SoilGrids250m (Hengl, Mendes de Jesus et al. 2017)). However, the data quality of GLiM can vary in different spatial locations depending on the quality of the original regional geological maps. GLiM consists of three levels, the first level contains 16 lithological classes, and the additional two levels describe more specific lithological characteristics. The GLiM is represented by 1,235,400 polygons; the polygons are converted to raster format for the basin-scale lithological type statistics. ~~For contiguous~~For China, the compiled regional data sources (China 1991, Xinjiang 1992, Survey 2001) have slightly lower resolutions than the GLiM target resolution (1:1 000 000). However, for a basin-scale study with a mean basin area of over 2000 km^2, the classification accuracy should satisfy most applications.



~~(a)~~ ~~(b)~~ ~~(c)~~



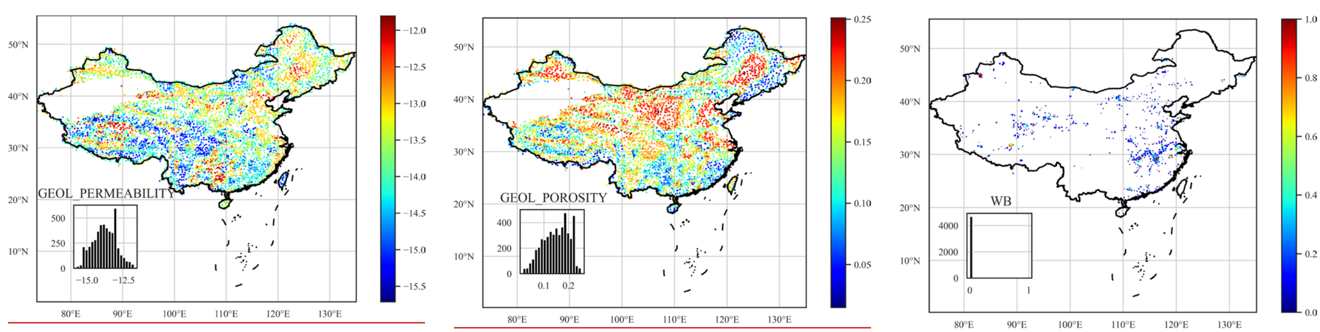
~~(a)~~ ~~(b)~~ ~~(c)~~



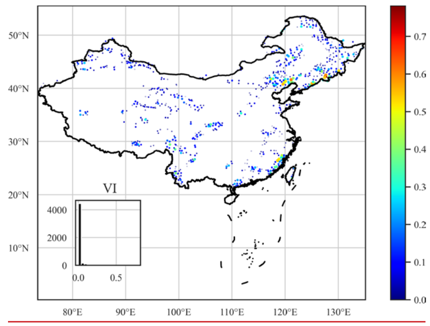
~~(a)~~ ~~(b)~~

~~**Figure 4. Maps of geological characteristics over contiguous China. The histograms indicate the number of catchments (out of 4875) in each bin.**~~

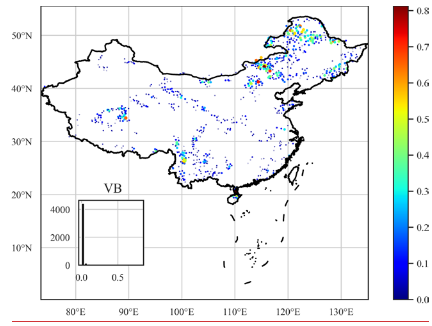
~~Compared to CAMELS and CAMELS-CL, one design consideration of the proposed dataset is that it should be more prepared for the data-driven research, such that we aim to generate as many types of catchment-scale data as possible since advanced data-driven methods can learn the representation of inputs automatically. To this end, we determined and recorded~~ Different from CAMELS and CAMELS-CL, we determined each lithological class's contribution to the catchment instead of recoding just the first and second most frequent classes. ~~The GLiM is represented by 1,235,400 polygons; the polygons are converted to raster format for the basin-scale lithological type statistics.~~



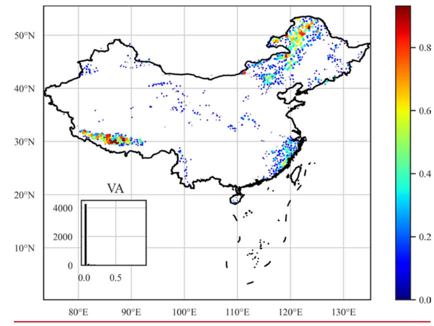
(a) (b) (c)



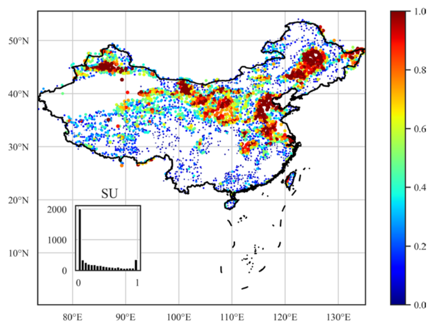
(a)



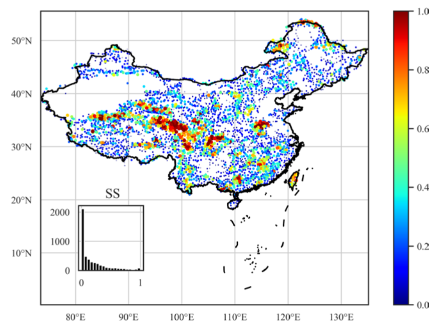
(b)



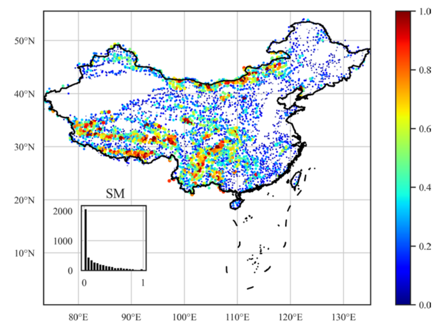
(c)



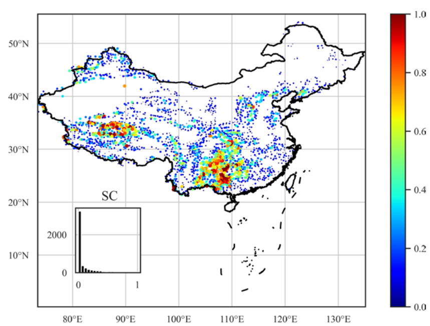
(d)



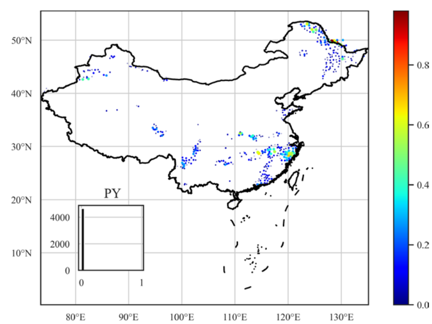
(e)



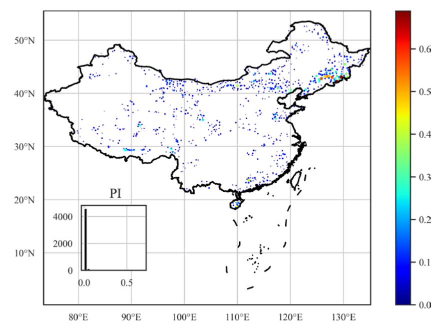
(f)



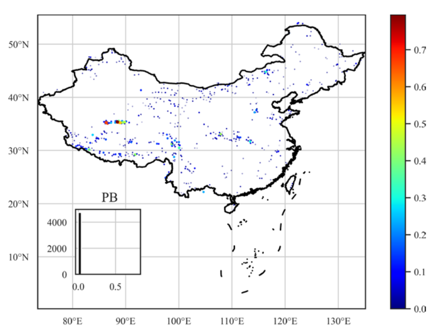
(g)



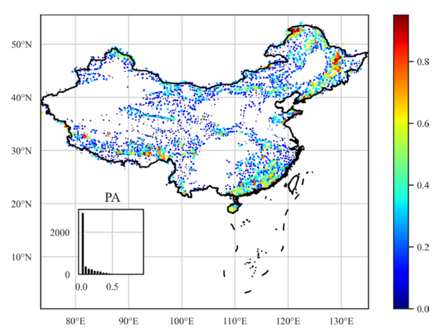
(h)



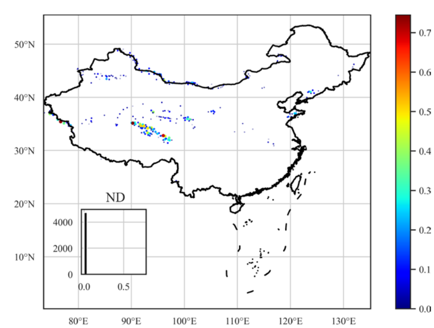
(i)



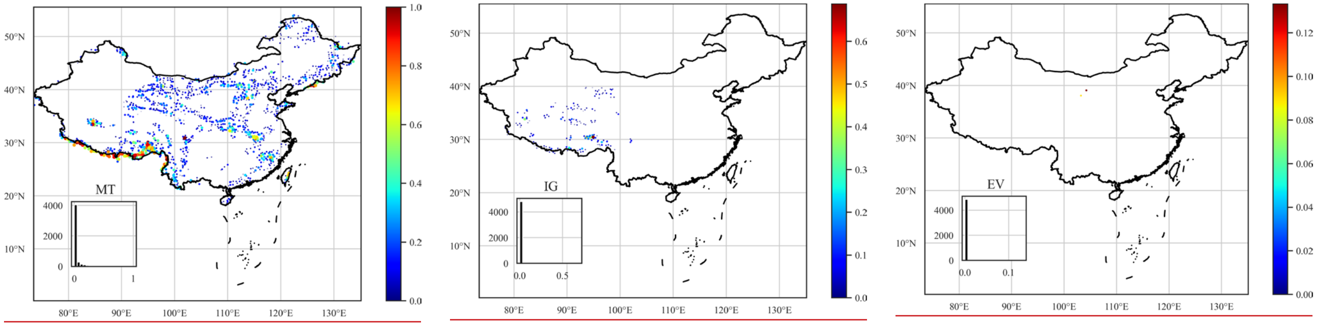
(j)



(k)



(l)



(m) (n) (o)

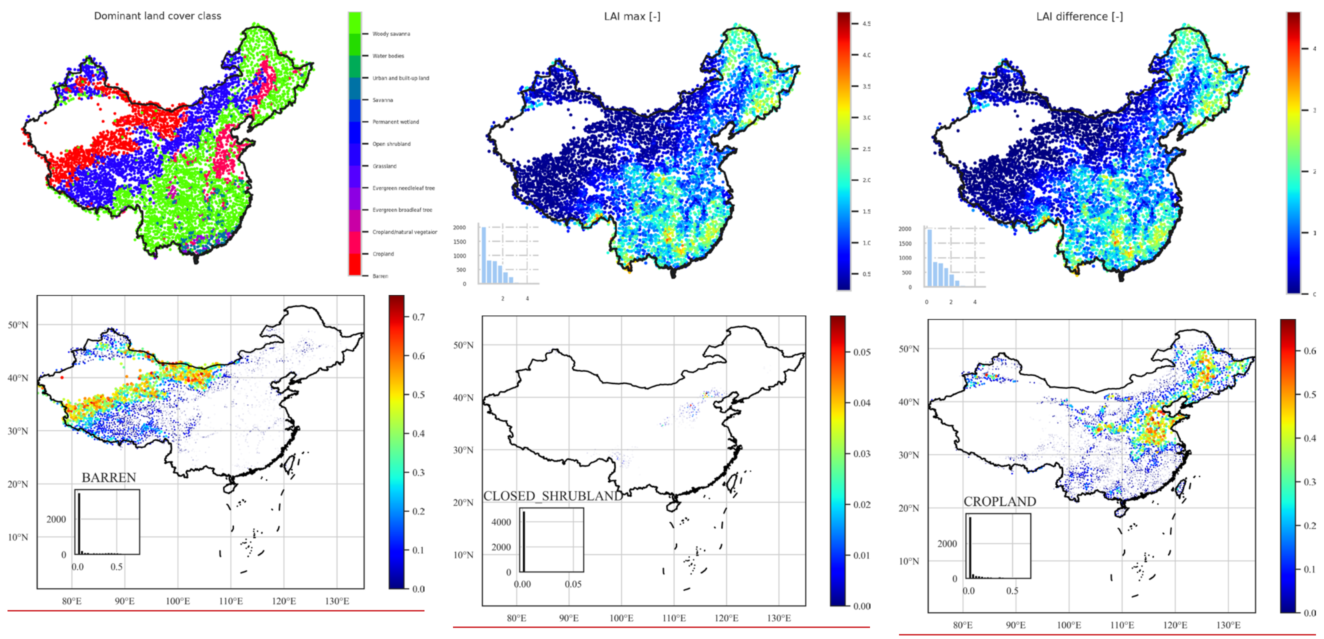
Figure 4: Distributions of geological characteristics over China. For lithologies, the plot size is scaled by the lithology proportion.

GLobal HYdrogeology MaPS (GLHYMPS) provides a global estimation of subsurface permeability and porosity, two critical characteristics for the soils' hydrological classification. Porosity and permeability influence an area's infiltration capacity. Soil with high porosity is likely to contain s amounts of water, and high permeable soil transmits water relatively quickly. Based on the high-resolution map of GLiM, which can differentiate fine and coarse-grained sediments and sedimentary rocks, GLHYMPS determined subsurface permeability depending on the different permeabilities of rock types. For the proposed dataset, we calculated the catchment arithmetic mean for porosity. Followed (Gleeson, Smith et al. 2011), the logarithmic scale geometric mean is used for representing subsurface permeability. The summary of geological characteristics is present in Table 3.

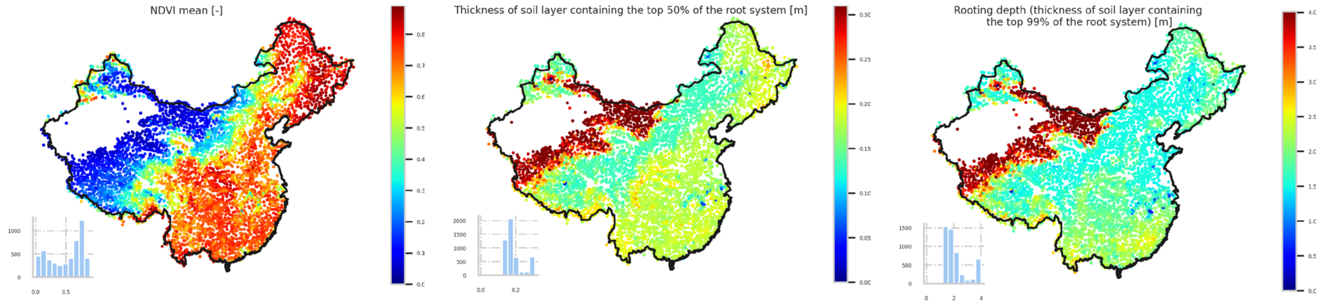
Porosity and permeability have similar distributions as geological classes. These two characteristics are highly dependent on rock properties, unconsolidated sediments, mixed sedimentary rocks, siliciclastic sedimentary rocks, carbonate sedimentary rocks, and acid plutonic rocks are the five most common geological classes in ~~contiguous~~ China. Unconsolidated sediment is the most common rock type in ~~contiguous~~ China, dominating 31.9% of catchments; it extends from Xinjiang to the inland of the northeast and the coastal area surrounding the Bohai Sea, due to the high proportion of unconsolidated sediments present in the rock, these areas typically have high permeability and medium porosity. Mixed sedimentary rocks are the second most common rock type in ~~contiguous~~ China, accounting for 20.3% of catchments, it dominated the southern Qinghai-Tibet Plateau, western Yunnan-Guizhou Plateau, and northern Inner Mongolia. These areas typically have high porosity and low permeability. Siliciclastic sedimentary rocks dominate 17.7% of basins, mainly distributed in the northern part of the Qinghai-Tibet Plateau and the junction of the Qinghai-Tibet Plateau and the Yunnan-Guizhou Plateau; there are also some distributions in the eastern inland. These areas have low subsurface permeability and high subsurface porosity. Amongst all catchments, 9.8% of catchments are dominated by carbonate sedimentary rocks. Carbonate sedimentary rocks are mainly located in eastern Yunnan and northern Qinghai-Tibet Plateau. Acid plutonic rocks are typically distributed in the mountains surrounding the inland northeast, namely the Daxinganling Mountain and the hills in southern Guangdong and southwestern Guangxi. They are also distributed along the Brahmiputra river in the south part of the Qinghai-Tibet Plateau. The distribution of Acid plutonic rocks is relatively scattered; there are many isolated Acid plutonic rocks distributions in different locations of ~~contiguous~~ China, accompanied by medium permeability and high porosity.

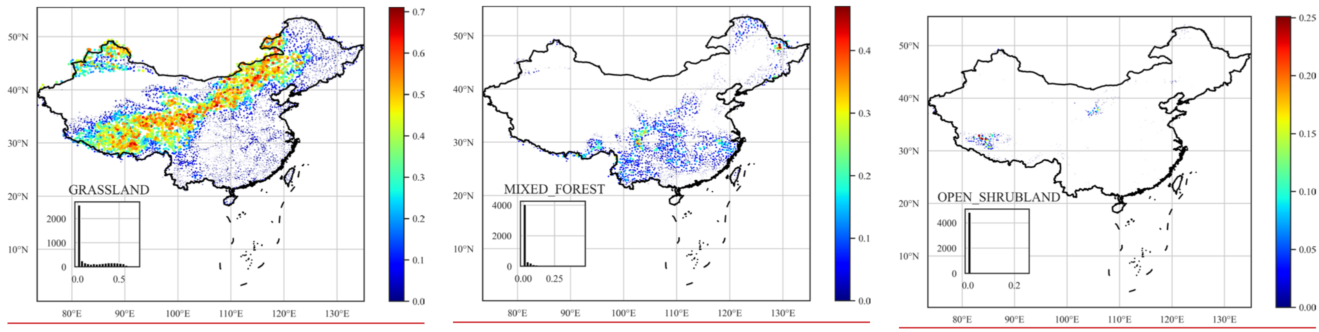
~~In summary, the~~The types of rocks in ~~contiguous~~ China are dominated by unconsolidated sediments and mixed sedimentary rocks. In 33.86% of the catchments, the dominant rock types occupy less than 50% of the catchment areas, and only 16.8% of basins are having a dominant rock type with an area fraction greater than 90%. Amongst ~~4875~~4911 basins, 9.4% of basins have prevalent rock types wholly occupying the area.

5 Landcover

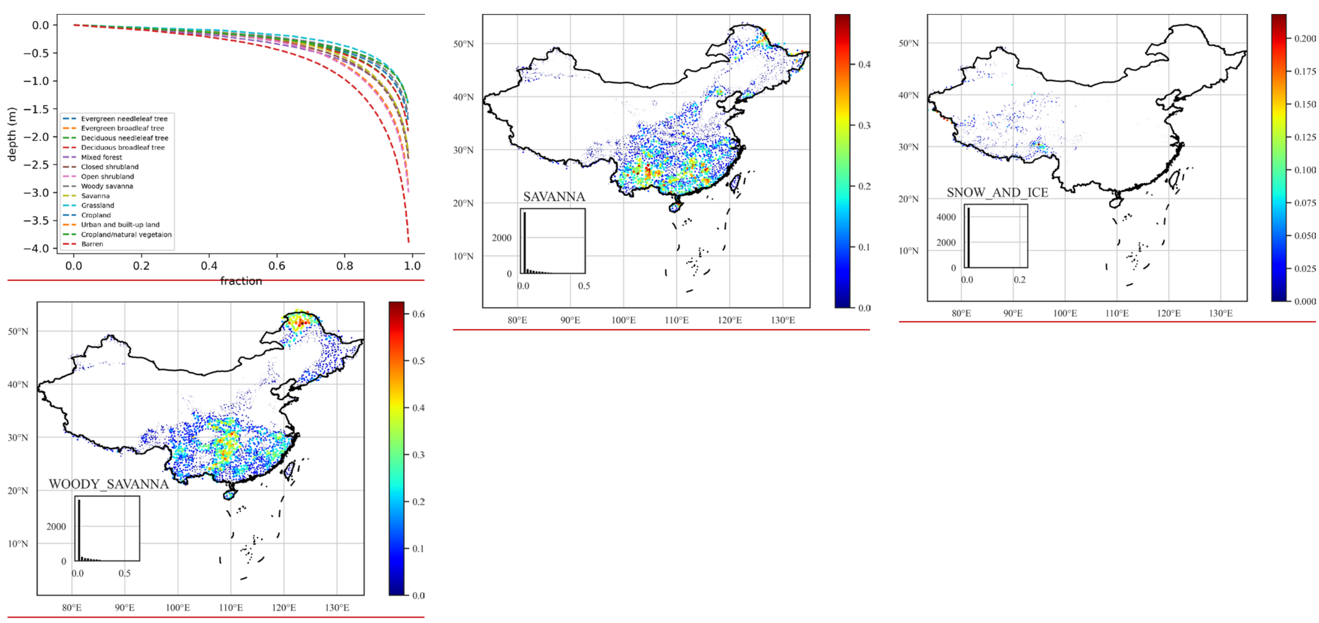


(a) (b) (c)

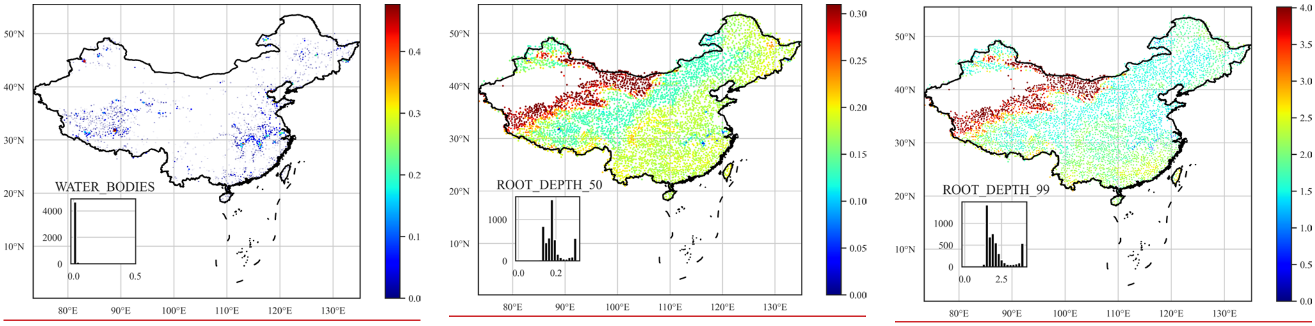

NDVI mean [-]
Thickness of soil layer containing the top 50% of the root system [m]
Rooting depth (thickness of soil layer containing the top 99% of the root system) [m]


GRASSLAND
MIXED_FOREST
OPEN_SHRUBLAND

(d) (e) (f)


depth (m)
fraction
Evergreen needleleaf tree
Evergreen broadleaf tree
Deciduous needleleaf tree
Deciduous broadleaf tree
Mixed forest
Closed shrubland
Open shrubland
Woody savanna
Savanna
Grassland
Cropland
Urban and built-up land
Cropland/natural vegetaion
Barren
SAVANNA
SNOW_AND_ICE
WOODY_SAVANNA

(g) (h) (i)



(j) (k) (l)

Figure 5~~. Maps~~: Distributions of land cover characteristics over ~~contiguous~~ China. ~~The histograms indicate~~For land cover types, the ~~number~~plot size is scaled by the size of ~~catchments (out of 4875) in each bin.~~ the land cover proportion.

We selected two indicators to characterize vegetation density and growth on the surface: Normalized difference vegetation index (NDVI) and Leaf area index (LAI). NDVI is an indicator with a valid range of -0.2 to 1, assessing whether the area being observed contains live green vegetation or the plants' health. However, NDVI is just a qualitative measurement of the vegetation density; it cannot provide a quantitative estimate of the vegetation density in the area. Moreover, NDVI often provides inaccurate vegetation density measurements, and only long-term measurement and comparison can ensure its accuracy. NDVI alone is not enough to estimate the state of plants in an area. Therefore, we have selected another indicator, LAI, to supplement the deficiencies of NDVI.

LAI is defined as the total needle surface area per unit ground area and half of the entire needle surface area per unit ground surface area. It is a quantifiable value. It is functionally related to many hydrological processes like water interception (van Wijk and Williams 2005). (Buermann, Dong et al. 2001) verifies the validity of LAI used to characterize vegetation growth. The data sources used are The Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (Didan 2015) for NDVI and Moderate Resolution Imaging Spectroradiometer (MODIS) (Myneni, Knyazikhin et al. 2015) for LAI. Followed (Addor, Newman et al. 2017), we determined maximum monthly LAI as an indicator characterising vegetation interception capacity and the maximum evaporative capacity and the difference between the maximum and minimum monthly LAI representing LAI's temporal variations.

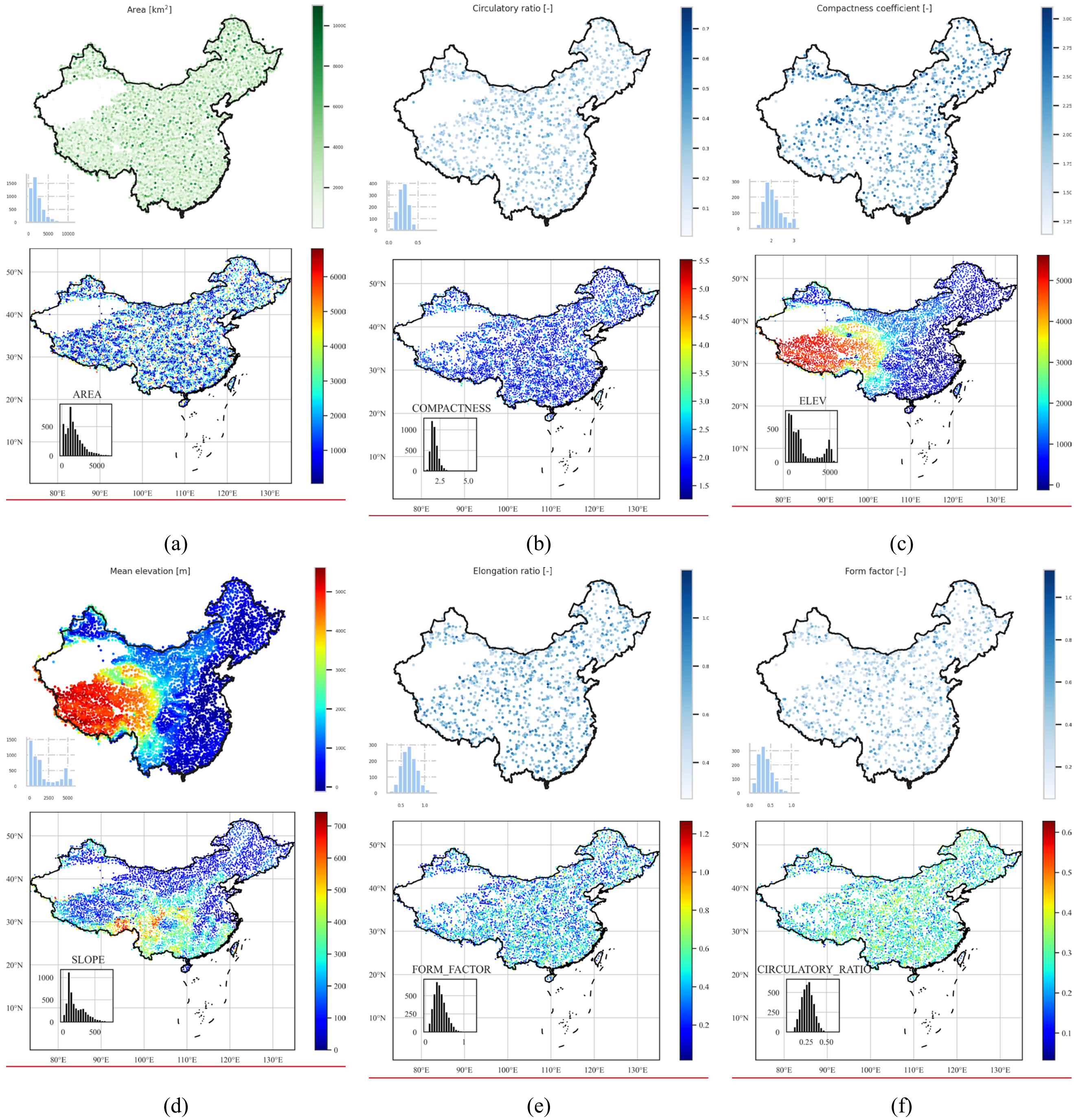
Land cover classification refers to segmenting the ground into different categories based on remote sensing images. The Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type provides different results depending on the classification system used. Annual International Geosphere-Biosphere Programme (IGBP) classification is used for building the dataset, which is derived by the c4.5 decision tree algorithm. The IGBP classification system was formulated by the IGBP Land Cover Working Group in 1995, resulting in 17 categories of land cover types (Belward, Estes et al. 1999). ~~(Friedl, Sulla-Menashe et al. 2010) compared the IGBP data of MODIS with other reference dataset~~Friedl, Sulla-Menashe et al. (2010) compared the IGBP data of MODIS with other reference datasets and concluded that the MODIS classification of IGBP has an accuracy of 75%. We determined the fraction of each land cover class for each basin based on the Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (Sulla-Menashe and Friedl 2018), which differentiates our dataset from CAMELS and CAMELS-CL (only calculated the proportion of the dominant types).

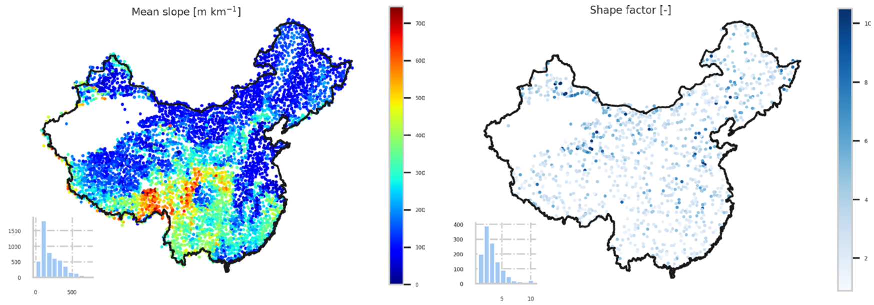
Followed (Addor, Newman et al. 2017), we ~~also~~ computed the average rooting depth (50% and 90%) for each catchment based on the IGBP classification using a two-parameter method (Zeng 2001). The root depth distribution of vegetation affects the ground's water holding capacity and the topsoil layer's annual evapotranspiration (Desborough 1997). Many models use root depth as an essential parameter to characterize soil moisture absorption capacity. (Zeng 2001) developed a two-parameter asymptotic equation for estimating root depth distribution; the root depth distribution is global, derived based on the IGBP classification avoiding the problem of significantly different root distributions in various research. Figure 5(g) shows root depth distributions of different vegetation types, based on (Zeng 2001)~~'s method.~~. The 90% root depth is usually considered to be "rooting depth", among the 17 categories of IGBP, cropland has the smallest rooting depth, and open shrubland has the largest. The 90% root depth of all vegetation is less than 2 meters. The national distribution of catchments soil characteristics is shown in Fig. 5.

6 Location and topography

The catchments' boundary files are obtained from the global drainage basin dataset (Masutomi, Inui et al. 2009). The ~~PDBD~~GDBD dataset was derived from digital elevation models (DEMs) with a high-resolution (100m-1km), and the errors were corrected by either automatic methods or manually. Additionally, ~~PDBD~~GDBD also provides population and population density estimates for catchments, and these two indicators are also included in our dataset as a measure of human intervention. Global ~~Runoff~~Streamflow Data Centre (Center 2005) discharge gauging stations were used for referencing the derived basins. ~~In contiguous China, PDBD~~GDBD has a high average match area rate (AMAR) and good geographic agreement with existing global drainage basin data in China. Based on the high-quality dataset, precise geographic and topographic information can be derived~~. See Fig. 6 for a summary~~.

The topography attributes of each catchment are determined based on the ASTGTM product retrieved from https://lpdaac.usgs.gov, maintained by the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC) at the USGS Earth Resources Observation and Science (EROS) Center.


Area [km^2]
Circulatory ratio [-]
Compactness coefficient [-]
AREA
COMPACTNESS
ELEV
(a)
(b)
(c)
Mean elevation [m]
Elongation ratio [-]
Form factor [-]
SLOPE
FORM_FACTOR
CIRCULATORY_RATIO
(d)
(e)
(f)



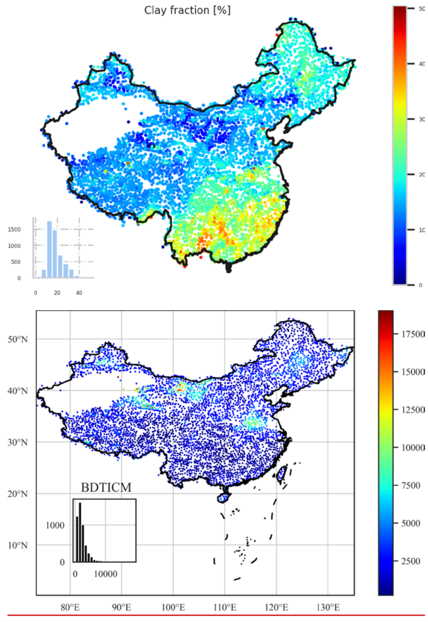
~~(g)~~ ~~(h)~~

Figure 6. ~~Maps~~Distributions of topographic characteristics~~ over contiguous China. The histograms indicate the number of catchments (out of 4875) in each bin~~.

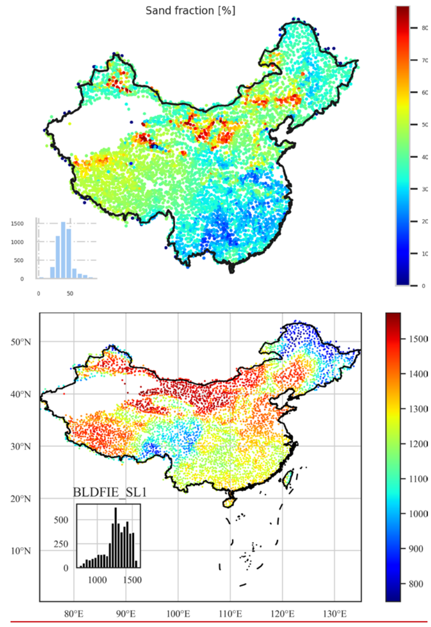
The CAMELS dataset ~~just~~ provides two parameters (two area estimates) for describing the catchment shape~~; however, the~~. The physical characteristics of a catchment can affect the ~~runoff~~streamflow volume and the ~~runoff~~streamflow hydrograph of the catchment under a storm. To provide a complete description of the catchment shape, we computed several geometrical parameters of the catchment related to the ~~runoff~~streamflow process~~,~~ (Fig. 6), including catchment form factor, shape factor, compactness coefficient, circulatory ratio and the elongation ratio (Subramanya 2013). A summary of the location and topography attributes can be found in Table 3.

7 Soil

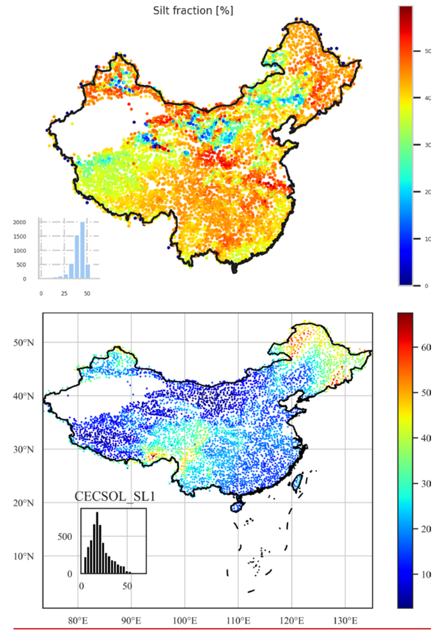
The proposed dataset has a total of 54 soil attributes (Table 3) derived from (Hengl, Mendes de Jesus et al. 2017), (Dai, Xin et al. 2019) and (Shangguan, Dai et al. 2013). ~~The summary result is shown in Fig. 7.~~ Five categories of soil characteristics (pH in H2O, organic carbon content, depth to bedrock, cation-exchange capacity, and bulk density) are determined from SoilGrids. SoilGrids (Hengl, Mendes de Jesus et al. 2017) provides global predictions for soil properties including organic carbon, bulk density, cation exchange capacity (CEC), pH, soil texture fractions and coarse fragments by fusing multiple data sources including MODIS land products, SRTM DEM, climatic images and global landform and lithology maps at the 250m resolution~~.~~ (Fig. 7). SoilGrids made predictions based on machine learning algorithms and many ~~covariates~~covariates' layers primarily derived from remote sensing data. SoilGrids has soil characteristics for several soil depths.


Clay fraction [%]
BDTICM

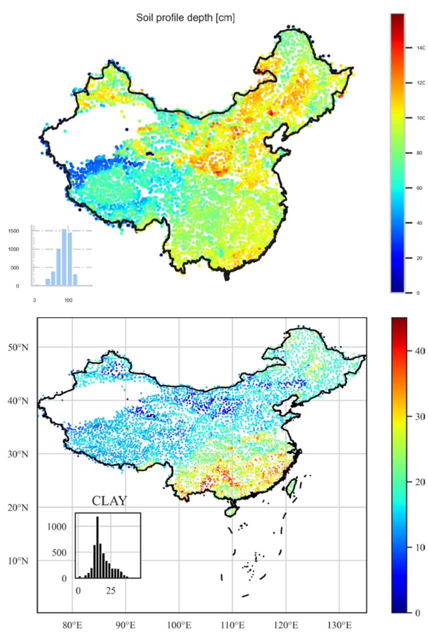
(a)


Sand fraction [%]
BLDFIE_SL1

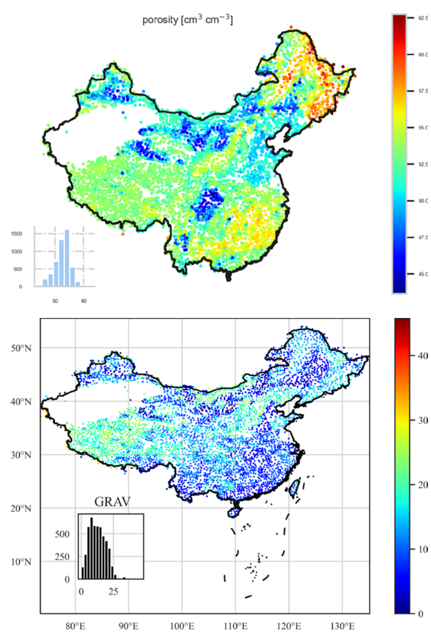
(b)


Silt fraction [%]
CECSOL_SL1

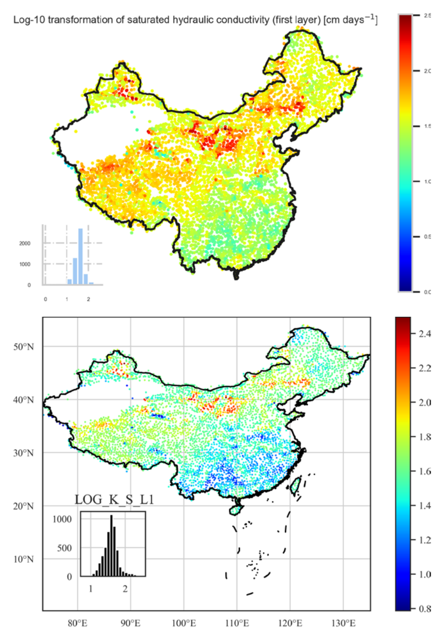
(c)


Soil profile depth [cm]
CLAY

(d)


porosity [cm^3 cm^{-3}]
GRAV

(e)


Log-10 transformation of saturated hydraulic conductivity (first layer) [cm days^{-1}]
LOG_K_S_L1

(f)

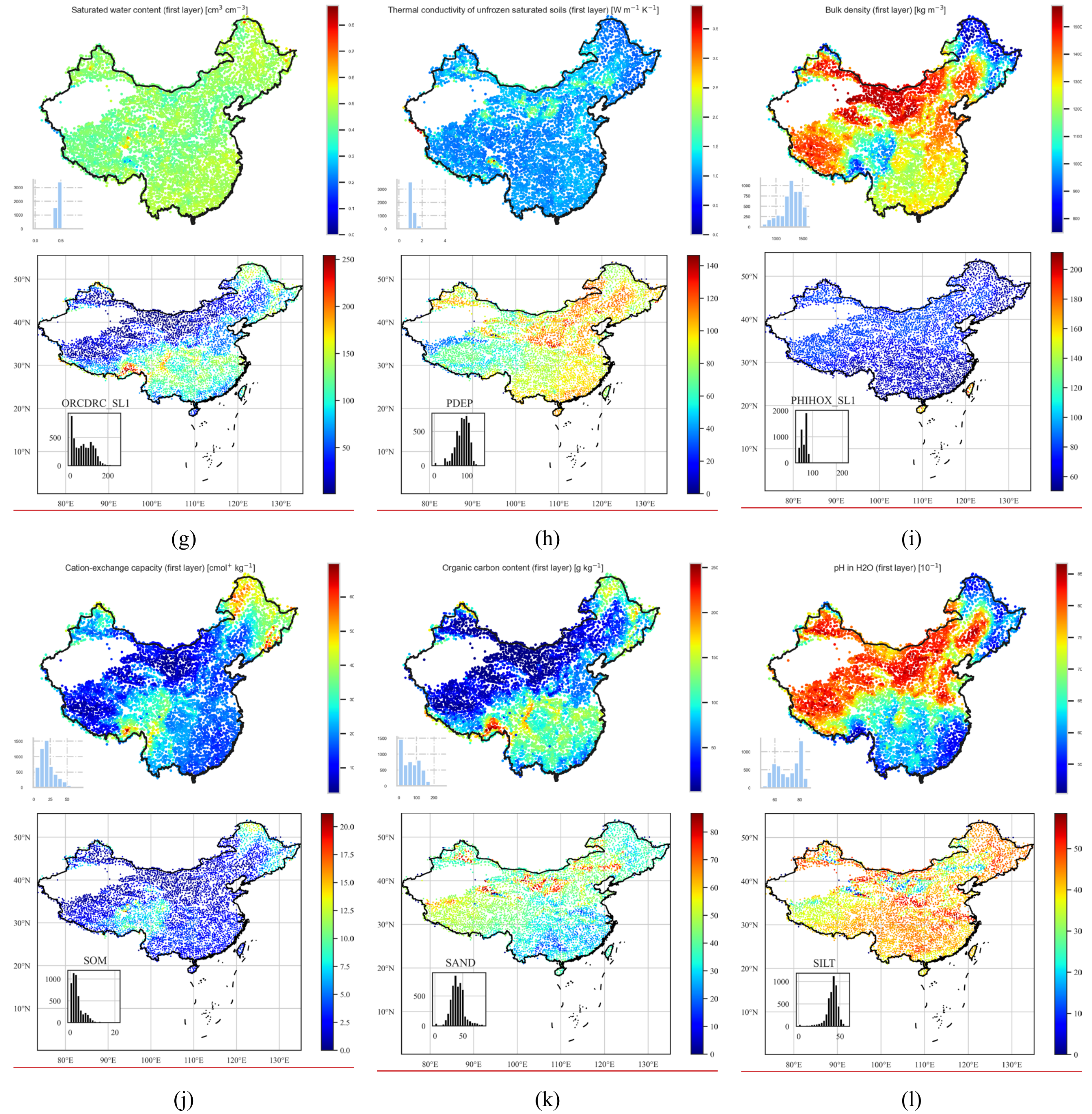


Figure 7~~. Maps~~: Distributions of soil characteristics over ~~contiguous~~ China. ~~The histograms indicate the number of catchments (out of 4875) in each bin.~~

~~Unlike~~Different from CAMELS, whose reported results are obtained by a linear weighted combination of the different soil layers, and CAMELS-BR, whose products are soil characteristics at a depth of 30cm. We computed soil characteristics at all soil layers provided by ~~SoilGrids such that advanced models can learn directly from the raw inputs~~SoilGrids250m.

~~To be consistent with CAMELS, we also~~We determined saturated water content and saturated hydraulic conductivity (Dai, Xin et al. 2019). ~~We also introduced thermal conductivity of unfrozen saturated soils (Dai, Xin et al. 2019). (Dai, Xin et al. 2019)~~Based on the same dataset, we also introduced the thermal conductivity of unfrozen saturated soils. Dai, Xin et al. (2019) provides a global estimation of soil hydraulic and thermal parameters using multiple Pedotransfer Functions (PTFs) based on ~~SoilGrids.~~the SoilGrids250m dataset. Based on the ~~SoilGrids~~SoilGrids250m and GSDE (Shangguan, Dai et al. 2014) datasets, ~~(Dai, Xin et al. 2019) produced six soil layers with a spatial resolution~~Dai, Xin et al. (2019) produced six soil layers with a spatial resolution of 30×30 arc-second. The vertical resolution of (Dai, Xin et al. 2019) is the same as the ~~SoilGrids~~SoilGrids250m, with six intervals of 0–0.05 m, 0.05–0.15 m, 0.15–0.30 m, 0.30–0.60 m, 0.60–1.00 m, and 1.00–2.00 m. ~~Same as the methods applied to SoilGrids, we determined~~We determine and ~~records~~record catchment soil characteristics for all these layers.

~~To provide even more complete description of the soil~~ In addition, we determined seven more soil characteristics (Shangguan, Dai et al. 2013) including soil profile depth, porosity, clay/silt/sand content, rock fragment, and soil organic carbon content. ~~(Shangguan, Dai et al. 2013)~~ Shangguan, Dai et al. (2013) provides physical and chemical attributes of soils derived from 8979 soil profiles at 30×30 arc-second resolution, the polygon linkage method was used to derive the spatial distribution of soil properties. The profile attribute database and soil map are linked under a framework avoiding uncertainty in taxon referencing.

Depth to bedrock controls many physical and chemical processes in soil. The distribution of depth to bedrock in ~~contiguous~~ China is characterised by (i) low in the mountainous areas, such as Yunnan province and Chongqing City; (ii) high in barren areas, e.g. North and Northwest China. The introduced soil pH value is crucial since it influences many other physical and chemical soil characteristics. The spatial variability of soil pH in ~~contiguous~~ China is characterised by (i) soils in southern ~~contiguous~~ China are acid to strongly acid; (ii) soils in northern China are natural or alkaline; (iii) soils in ~~north-eastern~~northeastern forested areas are also acid (pH < 7.2). Cation exchange capacity can be seen as a measure of soil fertility since it measures how much nutrient the soil can store such that it influences the growth of the ~~vegetations~~vegetation. Cation exchange capacity is positively correlated with soil organic matter content and clay content, which Cation exchange capacity is generally low in sandy and silty soils. The spatial variability of Cation exchange capacity in ~~contiguous~~ China is characterised by (i) high in peat and forested areas in Qinghai-Tibet Plateau, central and northeast China (ii) The Cation exchange capacity in the desert area such as the northwest is extremely low. Soil hydraulic and thermal properties are greatly affected by soil organic matter (SOM). Soil organic matter has a similar distribution to the cation exchange capacity: high in the peat and forested areas such as northeast China and low in the north and northwest.

8 Meteorological time series

Table 4: Summary table of catchment meteorological time series available in the proposed dataset

Variable	Description	Unit
prs	catchment daily averaged ground pressure	hPa
tem	catchment daily averaged temperature at 2 m above ground	°C
rhu	catchment daily averaged relative humidity	-
pre	catchment daily averaged precipitation	mm d^{-1}
evp	catchment daily averaged evaporation measured by ground instruments	mm d^{-1}
win	catchment daily averaged wind speed at 2 m above ground	m s^{-1}
ssd	catchment daily averaged sunshine duration	h d^{-1}
gst	catchment daily averaged ground surface temperature	°C
pet	catchment daily averaged potential evapotranspiration determined by Penman's equation (~~see~~ Appendix A)	mm d^{-1}

There have been many studies based on SURF_CLI_CHN_MUL_DAY in China (Liu, Xu et al. 2004, Xu, Gao et al. 2009, Huang, Han et al. 2016, Liu, Zheng et al. 2017), such as trend analysis of the pan evaporation (Liu, Yang et al. 2010). Still, there has not yet been a large-scale basin-oriented meteorological time series dataset in ~~contiguous~~ China. Researchers still need to do repeated works to extract historical meteorological data from the SURF_CLI_CHN_MUL_DAY dataset for the research. For the first time, we release a catchment~~-~~ scale meteorological time series dataset. ~~We will also~~The open-~~source the~~sourced code ~~for researchers to~~can generate any catchment's meteorological time series within ~~contiguous~~ China. The basin-oriented dataset provides meteorological time series for ~~4875~~4911 basins from 1990 to ~~2018~~2020 based on the China Meteorological Data Network. Meteorological time series includes pressure, temperature, relative humidity, precipitation, evaporation, wind speed, sunshine duration, ground surface temperature and potential evapotranspiration ~~(see~~ (Table 4 ~~for a summary).~~).

The meteorological time series data from 1951 to 2010 is derived based on the "1951-2010 China National Ground Station Data Corrected Monthly Data File Basic Data Collection" data construction project. Other data include monthly reported data to the National Meteorological Information Centre by the provinces, and hourly and daily data uploaded by automatic ground stations in real-time. ~~The SURF_CLI_CHN_MUL_DAY dataset is quality controlled, the quality and completeness of each variable are significantly improved compared to the previous similar products. M~~During the development of the dataset, missing data were filled by interpolating its nearest stations.

Figure 2 presents the variation of the ~~distribution~~number of ~~the observation~~ sites. The start date of the recording is 1951, but because the early site distribution is sparse, we only used records from 1990 to ~~2018~~2020 to construct the dataset to ensure the data quality. ~~The interpolation method used is the~~ Inverse distance weighting ~~since it~~ shows better performance than other ~~comparators. Catchment-scale raster is extracted from the interpolated national raster using the open-source rasterio[6] package. For all variables, we take the arithmetic mean on the extracted catchment raster as the catchment mean. Potential~~interpolation methods. In addition, potential evapotranspiration (PET) is estimated based on Penman's Equation (Appendix A) and other ~~catchment~~ meteorological variables.

~~9 Normal Camels YR – Normalized Catchment attributes and meteorology for Yellow River basin~~

~~Apart from the dataset providing the catchment attributes and meteorological forcing for contiguous China, we also offer a self-contained dataset covering the Yellow River basin with normalized streamflow measurements. The streamflow data are normalized to have zero mean and a standard deviation of 1 for each basin. The Normal-Camels-YR dataset is designed to support machine learning and deep learning research related to hydrology. In particular, fifty-four watersheds are less affected by human activities (selection is based on the Global Reservoirs and Dam databases (GRanD) (Lehner, Liermann et al. 2011) which provides the locations of reservoirs and dams globally), which makes them suitable for rainfall-runoff modelling research. For most machine learning and deep learning algorithms, data normalization will not affect model performance (e.g., neural network-based and tree-based algorithms). Besides, other research, such as trend analysis, can also be carried out. The Normal-Camels-YR dataset is self-contained to fully describe the Yellow River basin and is particularly helpful for the hydrology research of the Yellow River.~~

~~During the dataset development, basins with too few observations are removed, resulting in discontinuous basin identifiers. Normal-Camels-YR covers 102 gauges in the Yellow River basin, providing basin boundary shapefiles, static attributes and normalized streamflow measurements for each basin. The covered basins have areas ranging from 134 to 804,421 square kilometres. The time resolution of streamflow measurements is seven days, and the mean length of records of the streamflow measurements is 684, which means the mean period of the streamflow measurements for each basin is over 13 years. Meteorological variables included in Normal-Camels-YR is slightly different; it introduced daily maximum and minimum for some variables (Table 5).~~

[6] ~~https://github.com/mapbox/rasterio~~

9 HydroMLYR: Hydrology dataset for Machine Learning in YRB

In addition to the basin-wise static attributes provided in CCAM, we propose HydroMLYR, a hydrology dataset for machine learning research in the YRB (Fig. 1). HydroMLYR includes standardized streamflow measurements for 102 basins. The streamflow data is seven-day averaged and standardized basin-wise to have zero mean and a standard deviation of 1 (Fig. 8). The HydroMLYR dataset is proposed to support machine learning or deep learning hydrology research (e.g., neural network-based and tree-based algorithms). It can be used in two cases: (1) to develop machine learning models on the YRB or (2) when it is desirable to verify the generalization ability of a machine learning model on YRB.

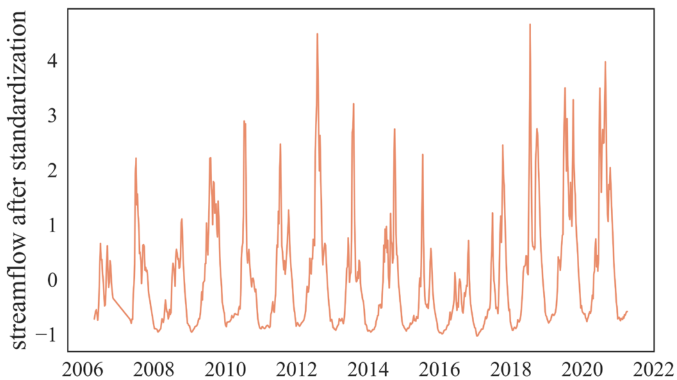


Figure 8: Examples of standardized runoff

The dataset provides 40 natural basins in the dataset which are not affected by reservoirs and dams. The selection is based on a newer version[7] of the Global Reservoirs and Dam databases (Lehner, Liermann et al. 2011) which provides the locations of reservoirs and dams globally. HydroMLYR covers 102 basins in the YRB, including basin boundary shapefiles, static attributes, and standardized streamflow measurements for each basin. The covered basins have areas ranging from 134 to 804,421 square kilometres. Therefore, modelling on a large scale of the YRB is also possible. Meteorological records in HydroMLYR introduced daily maximum and minimum for some forcing variables (Table 5).

The original streamflow observations are not continuous. The average record length is 11.3 years. Although the development of machine learning models does not necessarily require the data to be continuous, we separately provide continuous streamflow observations with an average record length of 8.3 years.

Table 5: Meteorological variables provided in ~~Normal-Camels-YR, the time series length is 22 years (1999-2020)~~HydroMLYR

Attribute name	Description	Unit
evp	catchment daily averaged evaporation (observations)	~~0.1~~ mm d^{-1}
gst_mean	catchment daily averaged ground surface temperature	~~0.1~~ °C

[7] http://globaldamwatch.org/data/#core_global

gst_min	catchment daily minimum ground surface temperature	~~0.1~~ °C
gst_max	catchment daily maximum ground surface temperature	~~0.1~~ °C
pre	catchment daily averaged precipitation	~~0.1~~ mm d^{-1}
prs_mean	catchment daily averaged ground surface pressure	~~0.1~~ hPa
prs_max	catchment daily maximum ground surface pressure	~~0.1~~ hPa
prs_min	catchment daily minimum ground surface pressure	~~0.1~~ hPa
rhu	catchment daily averaged relative humidity	-
ssd	catchment daily averaged sunshine duration	~~0.1~~ h
tem_mean	catchment daily averaged temperature	~~0.1~~ °C
tem_min	catchment daily minimum temperature	~~0.1~~ °C
tem_max	catchment daily maximum temperature	~~0.1~~ °C
win_max	catchment daily maximum wind speed	~~0.1~~ m s^{-1}
win_mean	catchment daily averaged wind speed	~~0.1~~ m s^{-1}

10 Data and code availability ~~and software packages used.~~

The proposed dataset is freely available at http://doi.org/10.5281/zenodo.~~4704017~~5137288. The files provided are (i) several separate files containing 120+ catchments attributes, (ii) the daily meteorological time series in a zip file, (iii) the catchment boundaries used to compute the attributes and extract the time series, (iv) the ~~Normal-Camels-YR~~HydroMLYR dataset, (v) an attribute description file and (v) a readme file. ~~The code used to generate the dataset is mainly based on several publicly available packages: rasterio, gdal~~ [8]~~, pyshp~~ [9]~~, geopandas~~ [10]~~, fiona~~ [11]~~, and xarray~~ [12]~~. Complement code for generating any watershed's dataset will be released soon.~~

11 Conclusion

The CCAM dataset proposed in this paper provides a novel dataset for hydrological research in ~~contiguous China. In the study~~ China.~~area, there is no catchment attributes dataset has been proposed before, either a catchment-scale time series~~

[8] ~~https://github.com/OSGeo/gdal~~

[9] ~~https://github.com/GeospatialPython/pyshp~~

[10] ~~https://github.com/geopandas/geopandas~~

[11] ~~https://github.com/Toblerity/Fiona~~

[12] ~~https://github.com/pydata/xarray~~

~~meteorological dataset.~~ All ~~catchments~~basins delaminated from the DEM are studied, covering ~~contiguous~~entire China. The dataset includes daily meteorological forcing time-series data including precipitation, temperature, potential evapotranspiration, wind, ground surface temperature, pressure, humidity, sunshine duration and derived potential evapotranspiration of ~~4875~~4911 catchments. The proposed time series dataset is derived based on the quality-controlled ~~site observation dataset,~~ SURF_CLI_CHN_MUL_DAY~~. We will also release the complement code for generating any shapefile's meteorological time series within contiguous China based on the SURF_CLI_CHN_MUL_DAY dataset (freely available for Chinese researchers). The dataset has longer time series (from 1990 to 2018) and more meteorological variables than the previously proposed datasets. The dataset also~~ dataset. CCAM includes 120+ catchment attributes, including soil, land cover, geology, climate indices and topography for each catchment. ~~-~~We produced a series of maps depicting the catchment attributes distributions in ~~contiguous~~ China. These maps present regional changes of various features; we also ~~describe~~estimate the relationships between them~~. The integration of~~ based on Kendall's correlation. Integrating multiple data sources into one dataset at a catchment~~-~~ scale ~~dramatically~~ simplifies the data compilation process in research. ~~Based on the dataset, we~~CCAM can help test hypotheses and formulate valid conclusions under various conditions, not just limited to a few specific locations~~. Together with the Normal-Camels-YR dataset, the proposed dataset can~~ and help explore how different basin characteristics influence hydrological behaviours, learn the migration of hydrological behaviours between different basins, and ~~to~~ develop general frameworks for large-scale model evaluation and benchmarking in China. A limitation of the study is the lack of estimation of the uncertainty of the meteorological time series. An alternative is to evaluate the uncertainty of the basin-wise meteorological data based on multiple independent data sources, but there are few data that provide as many data types as SURF_CLI_CHN_MUL_DAY. Hence, it poses a challenge for evaluating the uncertainty of these eight meteorological variables, which is left for future studies.

Appendix A: Modified Penman's equation

Penman's equation (Subramanya 2013), incorporating some modifications to the original formula, is:

$$PET = \frac{AH_n + E_a\gamma}{A + \gamma}$$

where PET is the daily potential evapotranspiration in mm per day; A is the slope of the saturation vapour pressure (ew) vs temperature (t) curve at the mean air temperature, in mm of mercury per Celsius; Hn is the net radiation in mm of evaporable water per day; Ea is a parameter including wind speed and saturation deficit; γ is the psychrometric constant = 0.49 mm of mercury per Celsius.

The relationship between ew and t is defined as:

$$e_w = 4.584 \exp\left(\frac{17.27t}{237.3 + t}\right)$$

The following equation estimates the net radiation:

$$H_n = H_a(1-r)\left(a+b\frac{n}{N}\right) - \sigma T_a^4\left(0.56-0.092\sqrt{e_a}\right)\left(0.10+0.90\frac{n}{N}\right)$$

where Ha is the incident solar radiation outside the atmosphere on a horizontal surface, expressed in mm of evaporable water per day (a function of the latitude and period of the year as indicated in Table A1); a is a constant depending upon the latitude ϕ and is given by $a = 0.29 \cos \phi$; b is a constant = 0.52; n is the sunshine duration in hours; N is the maximum possible hours of bright sunshine (a function of latitude, see Table A2); r is the reflection coefficient; σ is the Stefan-Boltzman constant = 2.01×10^{-9} mm/day; Ta is the mean air temperature in degrees kelvin; ea is the actual mean vapour pressure in the air in mm of mercury.

Table A1~~.~~: Mean Monthly Solar Radiation, Ha in mm of Evaporable Water/Day

North latitude	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0°	14.5	15.0	15.2	14.7	13.9	13.4	13.5	14.2	14.9	15.0	14.6	14.3
10°	12.8	13.9	14.8	15.2	15.0	14.8	14.8	15.0	14.9	14.1	13.1	12.4
20°	10.8	12.3	13.9	15.2	15.7	15.8	15.7	15.3	14.4	12.9	11.2	10.3
30°	8.5	10.5	12.7	14.8	16.0	16.5	16.2	15.3	13.5	11.3	9.1	7.9
40°	6.0	8.3	11.0	13.9	15.9	16.7	16.3	14.8	12.2	9.3	6.7	5.4
50°	3.6	5.9	9.1	12.7	15.4	16.7	16.1	13.9	10.5	7.1	4.3	3.0

The parameter Ea is estimated as:

$$E_a = 0.35\left(1+\frac{u_2}{160}\right)(e_w - e_a)$$

where $u2$ is the wind speed at $2m$ above ground in km/day; ew is the saturation vapour pressure at mean air temperature in mm of mercury; ea is the actual vapour pressure.

Table A2~~-~~: Mean Monthly Values of Possible Sunshine Hours, N

North latitude	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0°	12.1	12.1	12.1	12.1	12.1	12.1	12.1	12.1	12.1	12.1	12.1	12.1
10°	11.6	11.8	12.1	12.4	12.6	12.7	12.6	12.4	12.9	11.9	11.7	11.5
20°	11.1	11.5	12.0	12.6	13.1	13.3	13.2	12.8	12.3	11.7	11.2	10.9
30°	10.4	11.1	12.0	12.9	13.7	14.1	13.9	13.2	12.4	11.5	10.6	10.2
40°	9.6	10.7	11.9	13.2	14.4	15.0	14.7	13.8	12.5	11.2	10.0	9.4
50°	8.6	10.1	11.8	13.8	15.4	16.4	16.0	14.5	12.7	10.8	9.1	8.1

Appendix B: Correlation analysis of catchment attributes

To explore the potential connections between various types of watershed attributes, we did correlation analysis using the Kendall rank correlation coefficient (Kendall 1938). Kendall rank correlation coefficient is a measure of rank correlation: the similarity of the sort order of the two sets of data. Kendall correlation will be high if the orderings of the observations of two variables are similar. Kendall correlation avoids the assumption of linear relationship and that the distribution should be normal and continuous (e.g., Pearson correlation ~~coefficient; the results can be found in~~). When the relationship is not exactly linear, using Pearson correlation will miss out on information that Kendall could capture. Table B1~~, which~~ shows the top five most relevant attributes for each attribute~~, and the Fig. S1, the correlation matrix.~~. The analysis result shows that the correlations between variables are ~~consistent~~in line with general understanding, justifying the rationality of the dataset, to name a few:

(1) Subsurface permeability and porosity are ~~highly~~most correlated with geological attributes.

~~(2)~~ LAI and NDVI ~~have a high positive correlation (0.866).~~

~~(3)~~(2) ~~Root depth is~~are most positively correlated with each other but most negatively correlated with the fraction of barren land cover ~~types~~.

(3) Urban and built ups are most positively correlated with population density.

(4) In China, the savanna is mainly distributed in the southern coastal areas, resulting in that it is most positively correlated with ~~average rainfall (0.604).~~mean precipitation.

(5) Sand is most positively correlated with the saturated hydraulic conductivity ~~(0.86)~~ while the clay is strongly negatively correlated ~~(-0.763), and catchments~~ with ~~a lot of rainfall are less likely to have soil with high hydraulic conductivity (-0.647).~~.

~~(6) High altitude catchments tend to have lower saturated water content (-0.705).~~

Table B1~~.~~: The top five most relevant characteristics for each attribute (different soil layers for the same attribute are excluded, e.g~~.~~., phihox_sl2 is not included in the top five most relevant attributes of phihox_sl1 though they are highly correlated)

Attribute	1st	2nd	3rd	4th	5th
high_prec_freq	~~low_prec_dur~~root_depth_50(-0.~~58~~196)	~~root_depth_50(-~~grassland(0.~~438~~175)	root_depth_99(-0.~~436~~171)	~~barren(-~~som(0.~~39~~136)	~~pet_mean~~tksatu_l1(-0.~~261~~133)
high_prec_dur	~~elev(~~theta_s_l6(-0.~~544~~277)	theta_s_~~l6~~l5(-0.~~503~~234)	p_seasonality(~~prs_mean (-~~0.~~49~~233)	~~theta_s_l5(-~~elev(0.~~458~~211)	~~rhu_mean~~theta_s_l4(-0.~~431~~201)
low_prec_freq	pre_mean(-0.~~881~~766)	~~ssd_mean~~aridity(0.~~841~~745)	~~phihox_sl7~~ssd_mean(0.~~825~~652)	~~phihox_sl6(~~rhu_mean(-0.~~818~~627)	phihox_~~sl5~~sl7(0.~~814~~588)
low_prec_dur	~~barren~~aridity(0.~~728~~78)	~~rhu~~pre_mean(-0.~~723~~768)	~~evp~~ssd_mean(0.~~721~~731)	~~ndvi~~rhu_mean(-0.~~684~~709)	phihox_sl7~~root_depth_99~~(0.~~66~~579)

frac_snow_daily	~~tem~~gst_mean(-0.~~951~~802)	~~gst~~tem_mean(-0.~~949~~792)	~~ssd_mean~~lat(0.~~777~~575)	~~pre_mean~~evergreen_broadleaf_tree(-0.~~762~~512)	~~n_min(~~pre_mean(-0.~~703~~436)
prs_mean~~p_seasonality~~	~~pre_mean(~~elev(-0.~~901~~678)	~~rhu_mean~~lon(0.~~765~~552)	~~ssd~~rhu_mean~~(-~~(0.~~764~~432)	~~low_prec_freq(-0.712)~~urban_and_built-up_land(0.427)	~~frac_snow_daily~~barren(-0.~~683~~41)
~~pet~~pre_mean	~~cecsol_sl2~~aridity(-0.~~66~~913)	~~cecsol_sl1~~low_prec_dur(-0.~~634~~768)	~~cecsol_sl3~~low_prec_freq(-0.~~628~~766)	~~gst~~ssd_mean~~(~~(-0.~~622~~723)	~~bldfie_sl1~~rhu_mean(0.~~608~~712)
~~pre~~evp_mean	~~p_seasonality~~aridity(0.~~901~~643)	~~low_prec_freq~~ndvi_mean(-0.~~881~~632)	~~ssd~~rhu_mean(-0.~~858~~617)	~~rhu~~ssd_mean(0.~~832~~598)	~~phihox_sl7~~lai_dif(-0.~~819~~593)
~~tem~~gst_mean	~~gst~~tem_mean(0.~~992~~924)	frac_snow_daily(-0.~~951~~802)	~~pre_mean(~~lat(-0.~~747~~512)	~~ssd_mean(-0.709)~~evergreen_broadleaf_tree(0.507)	pet_mean~~p_seasonality~~(0.~~681~~442)
~~prs~~rhu_mean	~~elev~~aridity(-0.~~889~~751)	~~e_max(~~ssd_mean(-0.~~707~~746)	~~lon~~pre_mean(0.~~707~~712)	~~e_min(~~low_prec_dur(-0.~~707~~709)	~~rhu_mean(~~low_prec_freq(-0.~~603~~627)
~~rhu~~pet_mean	~~ssd_mean~~cecsol_sl2(-0.~~887~~451)	~~pre~~gst_mean(0.~~832~~442)	~~evp_mean~~cecsol_sl3(-0.~~823~~441)	~~ndvi_mean(~~cecsol_sl1(-0.~~813~~422)	~~low_prec_freq~~cecsol_sl4(-0.~~803~~42)
~~evp~~ssd_mean	~~ndvi_mean(-~~aridity(0.~~845~~753)	rhu_mean(-0.~~823~~746)	~~ssd_mean~~low_prec_dur(0.~~756~~731)	~~e_min~~pre_mean(-0.~~731~~723)	~~lon(-~~low_prec_freq(0.~~73~~652)
win_mean	ssd_mean(0.~~581~~426)	~~frac_snow_daily(~~woody_savanna(-0.~~571~~393)	tem_mean(-0.~~52~~379)	gst_mean(-0.~~507~~377)	~~low_prec_freq(~~mixed_forest(-0.~~477~~363)
~~ssd~~tem_mean	~~rhu~~gst_mean~~(-~~(0.~~887~~924)	~~pre_mean~~frac_snow_daily(-0.~~858~~792)	~~low_prec_freq~~evergreen_broadleaf_tree(0.~~841~~493)	~~frac_snow_daily~~pop_dnsty(0.~~777~~475)	~~p_seasonality~~lat(-0.~~764~~474)
p_seasonality ~~gst_mean~~	~~tem~~rhu_mean~~(~~(-0.~~992~~421)	~~frac_snow_daily~~tem_mean(-0.~~949~~397)	~~pre~~gst_mean~~(~~(-0.~~743~~393)	~~n_min(-~~ssd_mean(0.~~693~~393)	~~lat(-~~low_prec_dur(0.~~693~~375)
aridity~~geol_permeability~~	~~ss~~pre_mean(-0.~~408~~913)	~~sm(-~~low_prec_dur(0.~~403~~78)	~~su~~ssd_mean(0.~~399~~753)	~~se(~~rhu_mean(-0.~~323~~751)	~~bdticm~~low_prec_freq(0.~~24~~745)

slope~~geol_porosity~~	~~su(~~lat(-0.~~627~~374)	~~pa~~bdticm(-0.~~575~~348)	~~phihox_sl1(~~win_mean(-0.~~46~~341)	~~phihox_sl3~~mixed_forest(0.~~454~~341)	~~phihox_sl4~~evergreen_needleleaf_tree(0.~~453~~327)
~~ig~~lon	~~snow and ice(~~elev(-0.~~471~~585)	~~tksatu_l5~~prs_mean(0.~~324~~552)	~~tksatu_l3(~~evp_mean(-0.~~318~~5)	~~tksatu_l4(~~barren(-0.~~306~~482)	~~tksatu_l2~~ndvi_mean(0.~~275~~47)
elev~~pa~~	~~geol_porosity~~prs_mean(-0.~~575~~678)	~~phihox_sl1~~lon(-0.~~314~~585)	~~phihox_sl3~~urban_and_built-up_land(-0.~~302~~485)	~~phihox_sl2~~pop_dnsty(-0.~~301~~481)	~~phihox_sl4~~cropland(-0.~~297~~456)
~~se~~lat	~~geol_porosity(~~frac_snow_daily(0.~~362~~575)	~~geol_permeability(0.323)~~evergreen_broadleaf_tree(-0.548)	~~n_max~~gst_mean(-0.~~317~~512)	~~lat~~tem_mean(-0.~~317~~474)	~~n_min(~~low_prec_freq(0.~~316~~437)
~~su~~pop	~~geol_porosity~~urban_and_built-up_land(0.~~627~~618)	~~bdticm~~cropland(0.~~59~~519)	~~cropland(~~aridity(-0.~~468~~511)	~~phihox_sl1~~pre_mean(0.~~44~~505)	~~phihox_sl4~~rhu_mean(0.~~439~~492)
pop_dnsty~~sm~~	~~geol_permeability(-0.403)~~urban_and_built-up_land(0.639)	~~su~~aridity(-0.~~385~~538)	cropland~~(-~~(0.~~268~~533)	~~bdticm(~~pre_mean(0.~~23~~353)	~~e_max~~ssd_mean(-0.~~228~~521)
length~~vi~~	~~deciduous broadleaf tree~~area(0.~~214~~684)	~~geol_porosity~~form_factor(-0.~~18~~398)	~~lai_max~~shape_factor(0.~~165~~398)	~~lai_dif(~~elongation_ratio(-0.~~159~~398)	~~e_max~~compactness_coefficient(0.~~157~~363)
area~~mt~~	~~geol_porosity(~~length(0.~~412~~684)	~~evergreen needleleaf tree~~pop(0.~~327~~23)	~~oredre_sl3~~pa(0.~~265~~194)	~~oredre_sl4(~~circulatory_ratio(-0.~~258~~187)	~~bldfie_sl5(-0.254)~~compactness_coefficient(0.187)
~~ss~~form_factor	~~geol_permeability(-0.408)~~elongation_ratio(1.0)	~~su(~~shape_factor(-1.0~~.287~~)	~~sm(~~circulatory_ratio(0.~~206~~435)	~~geol_porosity(0.2)~~compactness_coefficient(-0.435)	~~tksatu_l6~~length(-0.~~156~~398)
~~pi~~shape_factor	~~deciduous broadleaf tree(0.299)~~elongation_ratio(-1.0)	~~geol_porosity(-0.208)~~form_factor(-1.0)	~~e_max(~~circulatory_ratio(-0.~~161~~435)	~~lon~~compactness_coefficient(0.~~161~~435)	~~e_min~~length(0.~~16~~398)
~~va~~compactness_coefficient	~~geol_porosity(-0.218)~~circulatory_ratio(-1.0)	~~high_prec_dur(~~elongation_ratio(-0.~~191~~435)	~~tem_mean(~~shape_factor(0.~~167~~435)	~~gst_mean~~form_factor(-0.~~16~~435)	~~su(~~length(0.~~16~~363)

circulatory_ratio~~wb~~	~~water bodies(0.674)~~compactness_coefficient(-1.0)	~~permanent wetland~~elongation_ratio(0.~~379~~435)	shape_factor~~root_depth_50~~(-0.~~164~~435)	~~theta_s_l3~~form_factor(0.~~148~~435)	~~theta_s_l4(~~length(-0.~~147~~363)
~~pb~~elongation_ratio	~~theta_s_l6(-~~shape_factor(-1.0~~.137~~)	~~theta_s_l5(-~~form_factor(1.0~~.133~~)	~~elev(m)(~~circulatory_ratio(0.~~124~~435)	~~theta_s_l4~~compactness_coefficient(-0.~~114~~435)	~~prs_mean~~length(-0.~~102~~398)
lai_dif~~vb~~	~~cecsol_sl2~~ndvi_mean(0.~~222~~808)	~~cecsol_sl3(~~barren(-0.~~213~~642)	~~cecsol_sl1(~~aridity(-0.~~212~~638)	~~cecsol_sl4~~pre_mean(0.~~211~~609)	~~cecsol_sl5~~woody_savanna(0.~~208~~607)
~~nd~~lai_max	~~snow and ice~~ndvi_mean(0.~~206~~779)	~~theta_s_l2~~barren(-0.~~154~~614)	~~theta_s_l3~~aridity(-0.~~151~~613)	~~theta_s_l1(-~~woody_savanna(0.~~144~~612)	~~tksatu_l4(~~phihox_sl2(-0.~~136~~602)
ndvi_mean~~py~~	~~phihox_sl1(-~~lai_dif(0.~~214~~808)	~~phihox_sl2(-~~lai_max(0.~~207~~779)	~~phihox_sl3~~barren(-0.~~207~~677)	~~phihox_sl4~~evp_mean(-0.~~205~~632)	~~phihox_sl5~~aridity(-0.~~202~~607)
root_depth_50~~ev~~	~~tksatu_l3(~~grassland(-0.~~07~~485)	~~tksatu_l4~~pet_mean(0.~~066~~232)	barren(0.~~064~~212)	high_prec_freq(-~~tksatu_l2(~~0.~~061~~196)	pdep(-~~tksatu_l1(~~0.~~061~~176)
root_depth_99~~lai_dif~~	~~ndvi_mean(~~grassland(-0.~~866~~339)	~~phihox_sl4(-~~barren(0.~~809~~337)	~~phihox_sl2~~cropland(-0.~~807~~336)	~~phihox_sl5~~pdep(-0.~~807~~284)	~~phihox_sl6~~lon(-0.~~807~~283)
~~lai_max~~evergreen_needleleaf_tree	~~ndvi_mean~~mixed_forest(0.~~856~~572)	~~phihox_sl4(-~~woody_savanna(0.~~815~~481)	phihox_~~sl5~~sl7(-0.~~814~~416)	phihox_sl6(-0.~~814~~411)	phihox_~~sl2~~sl5(-0.~~813~~409)
~~ndvi_mean~~evergreen_broadleaf_tree	~~lai_dif(~~lat(-0.~~866~~548)	~~lai_max(~~phihox_sl7(-0.~~856~~538)	~~evp_mean~~phihox_sl6(-0.~~845~~529)	~~rhu_mean(~~phihox_sl5(-0.~~813~~522)	~~barren(-~~pre_mean(0.~~772~~512)
~~root_depth_50~~deciduous_needleleaf_tree	~~barren~~cecsol_sl1(0.~~856~~274)	~~low_prec_dur(~~bldfie_sl1(-0.~~626~~274)	~~grassland(-~~cecsol_sl2(0.~~537~~272)	orcdrc_sl2(~~ndvi_mean(-~~0.~~513~~27)	~~evp_mean~~cecsol_sl3(0.~~497~~262)
~~root_depth_99~~deciduous_broadleaf_tree	~~barren~~mixed_forest(0.~~897~~604)	~~low_prec_dur~~woody_savanna(0.~~66~~568)	ndvi_mean~~(-~~(0.~~628~~524)	~~evp_mean~~lai_max(0.~~604~~5)	~~rhu_mean(-~~lai_dif(0.~~486~~497)
~~evergreen needleleaf~~	woody_savanna~~slope~~(0.~~398~~713)	~~bldfie_sl4(-0.391)~~deciduous_broadleaf_tree(0.604)	~~bldfie_sl5(-0.384)~~evergreen_n	~~bldfie_sl3~~phihox_sl7(-0.~~372~~565)	~~bldfie_sl7~~phihox_sl6(-0.~~366~~563)

~~tree~~mixed_forest			eedleleaf_tree(0.572)		
~~evergreen broadleaf tree~~closed_shrubland	~~pre_mean~~deciduous_broadleaf_tree(0.~~504~~217)	~~lai_max~~savanna(0.~~483~~16)	~~phihox_sl7(-~~mixed_forest(0.~~477~~158)	~~lai_dif(~~tksatu_l4(-0.~~471~~153)	~~phihox_sl6~~theta_s_l2(-0.~~47~~142)
~~deciduous needleleaf tree~~open_shrubland	~~woody savanna~~high_prec_dur(0.~~241~~179)	~~eecsol_sl2(~~rhu_mean(-0.~~231~~174)	~~oredre_sl2~~elev(0.~~226~~17)	~~pet~~ssd_mean~~(-~~(0.~~215~~17)	~~bldfie_sl1~~prs_mean(-0.~~214~~165)
~~deciduous broadleaf tree~~woody_savanna	~~lai_max~~mixed_forest(0.~~459~~713)	~~lai_dif(~~phihox_sl7(-0.~~452~~628)	~~eecsol_sl1(~~phihox_sl4(-0.~~433~~628)	~~bldfie_sl1~~phihox_sl3(-0.~~413~~627)	~~e_max(~~phihox_sl6(-0.~~361~~627)
~~mixed forest~~savanna	~~oredre_sl1~~pre_mean(0.~~501~~606)	~~lai_max~~cropland_natural_vegetaion(0.~~471~~605)	~~lai_dif~~woody_savanna(0.~~466~~604)	~~phihox_sl6~~aridity(-0.~~462~~602)	~~phihox_sl7~~ssd_mean(-0.~~461~~591)
~~closed shrubland~~grassland	~~theta_s_l1~~root_depth_50(-0.~~084~~485)	~~grav(0.079)~~cropland_natural_vegetaion(-0.363)	~~se(~~tem_mean(-0.~~075~~344)	~~theta_s_l2~~gst_mean(-0.~~072~~344)	~~urban and built-up land(0.064)~~root_depth_99(-0.339)
~~open shrubland~~permanent_wetland	~~high_prec_dur~~water_bodies(0.~~155~~469)	~~theta_s_l6(-~~savanna(0.~~151~~363)	~~rhu_mean(-0.149)~~urban_and_built-up_land(0.347)	~~prs~~pre_mean~~(-~~(0.~~147~~343)	~~evp_mean~~pop(0.~~139~~343)
~~woody savanna~~cropland	~~lai_max~~urban_and_built-up_land(0.~~633~~546)	~~lai_dif~~pop_dnsty(0.~~631~~533)	~~phihox_sl7(-~~pop(0.~~592~~519)	~~phihox_sl6~~elev(-0.~~59~~456)	lon(~~phihox_sl5(-~~0.~~585~~417)
~~savanna~~urban_and_built-up_land	~~pre_mean~~pop_dnsty(0.~~604~~639)	~~phihox_sl7(-~~pop(0.~~55~~618)	~~clay~~cropland(0.~~547~~546)	~~phihox_sl6~~elev(-0.~~543~~485)	~~phihox_sl5(-0.537)~~cropland_natural_vegetaion(0.428)
~~grassland~~cropland_natural_vegetaion	~~root_depth_50(-~~savanna(0.~~537~~605)	~~tem~~rhu_mean~~(-~~(0.~~496~~546)	~~gst_mean~~aridity(-0.~~491~~523)	~~frac_snow_daily(~~ssd_mean(-0.~~469~~52)	~~phihox_sl6~~pre_mean(0.~~438~~51)

~~permanent wetland~~snow_and_ice	~~wb~~ig(0.~~379~~431)	~~water bodies~~barren(0.~~349~~379)	~~p_seasonality(~~lon(-0.~~3~~373)	~~pre_mean~~elev(0.~~248~~369)	~~pop_dnsty(~~pdep(-0.~~23~~354)
~~cropland~~barren	~~su(~~ndvi_mean(-0.~~468~~677)	~~lon(~~lai_dif(-0.~~412~~642)	~~e_min(~~lai_max(-0.~~412~~614)	~~e_max~~aridity(0.~~412~~581)	evp_mean(~~elev(-~~0.~~388~~574)
~~urban and built-up land~~water_bodies	~~pop_dnsty~~permanent_wetland(0.~~811~~469)	~~pop~~wb(0.~~399~~39)	~~p_seasonality~~cropland_natural_vegetaion(0.~~286~~17)	~~tem_mean~~urban_and_built-up_land(0.~~261~~158)	elev(-0.~~244~~154)
geol_permeability~~cropland/natural vegetaion~~	~~ssd_mean~~sm(-0.~~458~~345)	~~savanna~~su(0.~~381~~326)	~~rhu_mean(~~ss(-0.~~371~~316)	~~frac_snow_daily(-~~bdticm(0.~~367~~228)	~~tem_mean~~pdep(0.~~364~~161)
geol_porosity~~snow and ice~~	~~tksatu_l5~~su(0.~~568~~455)	~~tksatu_l3(~~pa(-0.~~561~~417)	~~tksatu_l4(~~woody_savanna(-0.~~533~~323)	~~tksatu_l2~~phihox_sl3(0.~~506~~315)	~~tksatu_l1~~phihox_sl4(0.~~503~~314)
~~barren~~ig	~~root_depth_99~~snow_and_ice(0.~~897~~431)	~~root_depth_50~~elev(0.~~856~~194)	~~ndvi_mean~~theta_s_l2(-0.~~772~~185)	~~low_prec_dur(~~pdep(-0.~~728~~184)	~~evp_mean(~~theta_s_l3(-0.~~698~~182)
~~water bodies~~pa	~~wb(~~geol_porosity(-0.~~674~~417)	~~permanent wetland~~mt(0.~~349~~3)	~~root_depth_50(-~~pi(0.~~192~~295)	~~root_depth_99(-~~va(0.~~154~~271)	~~theta_s_l3~~vi(0.~~153~~246)
sc~~length~~	~~area(~~geol_porosity(-0.~~849~~285)	~~circulatory_ratio~~lat(-0.~~491~~264)	~~elongation_ratio~~bdticm(-0.~~451~~26)	~~form_factor(-~~slope(0.~~436~~246)	~~compactness_coefficient~~mixed_forest(0.~~292~~231)
~~area~~su	~~length~~bdticm(0.~~849~~52)	~~pop~~geol_porosity(0.~~418~~455)	~~circulatory_ratio~~woody_savanna(-0.~~255~~349)	~~cecsol_sl1~~geol_permeability(0.~~142~~326)	~~bldfie_sl2(-~~phihox_sl7(0.~~138~~326)
~~form_factor~~sm	~~elongation_ratio(~~geol_permeability(-0.~~992~~345)	~~circulatory_ratio(~~su(-0.~~647~~283)	~~shape_factor~~bdticm(-0.~~506~~228)	~~length~~cropland(-0.~~436~~199)	~~compactness_coefficient(-0.383)~~elev(0.194)
~~shape_factor~~vi	~~compactness_coefficient~~pa(0.~~786~~246)	~~elongation_ratio(-~~pi(0.~~566~~203)	~~form_factor(-~~va(0.~~506~~171)	~~circulatory_ratio~~geol_porosity(-0.~~372~~169)	~~length~~deciduous_broadleaf_tree(0.~~266~~166)
~~compactness_coefficient~~mt	~~shape_factor~~pa(0.~~786~~3)	geol_porosity~~circulatory_ratio~~(-0.~~594~~286)	~~elongation_ratio(-~~pi(0.~~421~~199)	~~form_factor(-0.383)~~deciduous_broadleaf_tree(0.187)	~~length~~area(0.~~292~~18)

~~circulatory_ratio~~ss	~~elongation_ratio(~~geol_permeability(-0.~~651~~316)	~~form_factor(~~su(-0.~~647~~17)	~~compactness_coefficient~~bdticm(-0.~~594~~136)	~~length(-0.491)~~evergreen_needleleaf_tree(0.106)	~~shape_factor~~tksatu_l6(-0.~~372~~096)
~~elongation_ratio~~pi	~~form_factor~~pa(0.~~992~~295)	~~circulatory_ratio~~vi(0.~~651~~203)	~~shape_factor(-~~mt(0.~~566~~199)	~~length~~geol_porosity(-0.~~451~~183)	~~compactness_coefficient(-0.421)~~va(0.172)
~~elev(m)~~va	~~prs_mean(-~~pa(0.~~889~~271)	~~e_min~~geol_porosity(-0.~~753~~219)	~~lon(-~~vb(0.~~752~~21)	~~e_max(-0.752)~~deciduous_needleleaf_tree(0.186)	~~theta_s_l4(-~~pi(0.~~7~~172)
~~slope(m/km)~~wb	~~n_min(-~~water_bodies(0.~~552~~39)	~~lat(-~~permanent_wetland(0.~~551~~264)	~~n_max(-~~bldfie_sl4(0.~~55~~148)	~~phihox_sl7(-~~bldfie_sl5(0.~~491~~147)	~~orcdrc_sl1~~urban_and_built-up_land(0.~~49~~138)
~~n_min~~pb	~~lat(1.~~mt(0.176)	~~frac_snow_daily~~pa(0.~~703~~132)	~~gst_mean~~theta_s_l5(-0.~~693~~128)	~~pre_mean(-~~area(0.~~651~~127)	~~tem_mean(-~~length(0.~~648~~123)
~~n_max~~vb	~~lat(1.~~va(0.21)	~~frac_snow_daily(~~geol_porosity(-0.~~701~~171)	~~gst_mean(-~~vi(0.~~692~~165)	~~pre_mean(-~~cecsol_sl7(0.~~65~~161)	~~tem_mean(-~~cecsol_sl6(0.~~647~~157)
~~e_min~~nd	~~lon(1.~~barren(0.154)	~~elev(-~~aridity(0.~~753~~146)	~~evp~~pre_mean(-0.~~731~~144)	~~prs_mean(~~lai_dif(-0.~~707~~141)	~~ndvi_mean~~snow_and_ice(0.~~691~~141)
~~e_max~~py	~~lon(1.~~phihox_sl1(-0.237)	~~elev~~phihox_sl2(-0.~~752~~233)	~~evp_mean~~phihox_sl3(-0.~~729~~233)	~~prs_mean(~~phihox_sl4(-0.~~707~~23)	~~ndvi_mean~~woody_savanna(0.~~69~~227)
~~pop(people)~~ev	~~area~~barren(0.~~418~~036)	~~urban and built up land(0.399)~~orcdrc_sl5(-0.035)	~~tem_mean(~~orcdrc_sl4(-0.~~318~~035)	~~p_seasonality(~~cecsol_sl3(-0.~~317~~034)	~~frac_snow_daily~~orcdrc_sl7(-0.~~304~~034)
tksatu_l1~~pop_dnsty(people/km²)~~	~~urban and built up land(0.811)~~grav(-0.346)	~~p_seasonality(~~som(-0.~~426~~344)	~~tem_mean~~bldfie_sl3(0.~~412~~298)	~~gst_mean~~bldfie_sl1(0.~~395~~295)	~~frac_snow_daily(-~~bldfie_sl2(0.~~39~~291)
tksatu_l2~~lon~~	~~e_max(1.~~som(-0.365)	~~e_min(1.~~bldfie_sl3(0.326)	~~elev(-~~bldfie_sl1(0.~~752~~326)	~~evp_mean(-~~bldfie_sl2(0.~~73~~323)	~~prs_mean(~~grav(-0.~~707~~308)
~~lat~~tksatu_l3	~~n_min(1.~~som(-0.344)	~~n_max(1.~~bldfie_sl2(0.328)	~~frac_snow_daily~~bldfie_sl1(0.~~702~~325)	~~gst_mean(-~~bldfie_sl3(0.~~693~~324)	~~pre_mean(-~~bldfie_sl4(0.~~651~~308)

tksatu_~~11~~l4	~~snow and ice~~bldfie_sl2(0.~~503~~398)	~~silt~~som(-0.~~465~~397)	~~som(-~~bldfie_sl1(0.~~366~~388)	~~sand~~bldfie_sl3(0.~~362~~384)	~~log_k_s_l5~~bldfie_sl4(0.~~327~~358)
tksatu_~~12~~l5	~~snow and ice~~bldfie_sl3(0.~~506~~386)	~~silt(-~~bldfie_sl2(0.~~49~~376)	~~sand(~~som(-0.~~406~~369)	~~som(-~~bldfie_sl4(0.~~365~~364)	~~log_k_s_l5~~bldfie_sl1(0.~~364~~358)
tksatu_~~13~~l6	~~snow and ice~~bldfie_sl3(0.~~561~~366)	som~~silt~~(-0.~~489~~362)	~~sand~~bdticm(0.~~409~~36)	~~ndvi_mean(-~~bldfie_sl2(0.~~368~~343)	~~clay(-~~bldfie_sl7(0.~~334~~338)
~~tksatu_14~~log_k_s_l1	~~snow and ice~~sand(0.~~533~~71)	~~silt~~clay(-0.~~49~~59)	~~sand(~~savanna(-0.~~465~~441)	~~ndvi_mean~~silt(-0.~~455~~436)	~~log_k_s_l5(~~rhu_mean(-0.~~414~~423)
~~tksatu_15~~log_k_s_l2	~~snow and ice~~sand(0.~~568~~709)	~~silt~~clay(-0.~~402~~578)	~~ndvi_mean~~savanna(-0.~~375~~452)	~~sand~~phihox_sl7(0.~~348~~438)	~~lai_dif~~silt(-0.~~326~~433)
~~tksatu_16~~log_k_s_l3	~~snow and ice~~sand(0.~~449~~682)	~~bdticm(~~clay(-0.~~403~~592)	~~log_k_s_l6(~~savanna(-0.~~384~~448)	~~su~~phihox_sl7(0.~~38~~442)	~~low_prec_freq~~phihox_sl6(0.~~364~~35)
log_k_s_~~11~~l4	sand(0.~~858~~612)	clay(-0.~~733~~603)	~~pre_mean~~savanna(-0.~~553~~49)	~~phihox_sl7(~~pre_mean(-0.~~551~~489)	phihox_~~sl6~~sl7(0.~~546~~485)
log_k_s_~~12~~l5	~~sand(~~clay(-0.~~865~~61)	~~clay(~~sand(0.~~729~~555)	phihox_sl7(0.~~575~~506)	~~phihox_sl6(~~savanna(-0.~~569~~501)	~~pre_mean(-~~phihox_sl6(0.~~568~~501)
log_k_s_~~13~~l6	~~sand(~~clay(-0.~~859~~563)	~~clay~~pre_mean(-0.~~728~~555)	~~pre_mean(-~~aridity(0.~~571~~548)	phihox_sl7(0.~~571~~534)	phihox_sl6(0.~~565~~532)
~~log_k~~theta_s_~~l4~~l1	~~sand(~~grav(-0.~~825~~82)	clay~~(~~(0.~~752~~325)	~~pre_mean~~sand(-0.~~647~~315)	~~phihox_sl7(~~elev(-0.~~636~~314)	~~phihox_sl6~~pdep(0.~~63~~311)
~~log_k~~theta_s_~~l5~~l2	~~sand(~~grav(-0.~~773~~585)	~~clay(~~pdep(0.~~714~~377)	~~phihox_sl7(~~elev(-0.~~654~~366)	clay~~phihox_sl6~~(0.~~649~~35)	~~phihox_sl5(~~sand(-0.~~646~~326)
~~log_k~~theta_s_~~l6~~l3	grav(-~~sand(~~0.~~688~~522)	~~clay(~~pdep(0.~~687~~42)	~~phihox_sl7(~~elev(-0.~~665~~414)	~~phihox_sl6~~prs_mean(0.~~662~~365)	~~pre_mean(-~~clay(0.~~662~~359)
theta_s_~~11~~l4	grav(-0.~~705~~515)	~~elev(~~pdep(0.~~422~~463)	~~rhu_mean(~~elev(-0.~~407~~412)	~~clay~~prs_mean(0.~~401~~349)	~~pdep~~lon(0.~~43~~28)
theta_s_~~12~~l5	grav(-0.~~713~~433)	elev(-0.~~505~~401)	pdep(0.~~475~~376)	~~e_min(~~sand(-0.~~442~~349)	~~lon~~rhu_mean(0.~~441~~331)

theta_s_~~l3~~l6	~~grav(-0.662)~~evergreen_broadleaf_tree(0.372)	~~elev~~grav(-0.~~638~~357)	~~prs_mean(~~elev(-0.~~554~~344)	~~pdep(~~sand(-0.~~52~~343)	~~e_min~~tem_mean(0.~~516~~337)
~~theta_s_l4~~orcdrc_sl7	~~elev~~bldfie_sl4(-0.~~7~~581)	~~grav~~bldfie_sl5(-0.~~663~~572)	~~prs_mean(~~bldfie_sl6(-0.~~594~~548)	~~pdep(~~bldfie_sl3(-0.~~571~~535)	~~e_min(~~bldfie_sl7(-0.~~51~~523)
~~theta_s_l5~~orcdrc_sl3	~~elev~~bldfie_sl3(-0.~~656~~738)	~~grav~~bldfie_sl2(-0.~~584~~728)	~~prs_mean(~~bldfie_sl1(-0.~~536~~701)	~~pdep(~~bldfie_sl4(-0.~~501~~691)	~~rhu_mean(~~bldfie_sl5(-0.~~467~~621)
~~theta_s_l6~~orcdrc_sl4	~~elev~~bldfie_sl3(-0.~~637~~702)	~~prs_mean(~~bldfie_sl2(-0.~~525~~682)	~~grav~~bldfie_sl4(-0.~~513~~676)	bldfie_sl1~~high_prec_dur~~(-0.~~503~~657)	~~rhu_mean(~~bldfie_sl5(-0.~~475~~614)
orcdrc_~~sl7~~sl5	~~cecsol_sl2(~~bldfie_sl4(-0.~~758~~641)	bldfie_~~sl2~~sl3(-0.~~745~~636)	bldfie_~~sl4~~sl2(-0.~~744~~611)	bldfie_~~sl1~~sl5(-0.~~737~~6)	~~cecsol_sl3(~~bldfie_sl1(-0.~~735~~592)
orcdrc_~~sl3~~sl6	bldfie_~~sl2~~sl4(-0.~~876~~584)	bldfie_~~sl4~~sl5(-0.~~875~~567)	bldfie_~~sl3~~sl6(-0.~~874~~556)	bldfie_~~sl5~~sl3(-0.~~849~~552)	bldfie_~~sl1~~sl7(-0.~~848~~534)
orcdrc_~~sl4~~sl2	bldfie_~~sl4~~sl2(-0.~~823~~787)	bldfie_~~sl2~~sl1(-0.~~809~~769)	bldfie_sl3(-0.~~803~~749)	bldfie_~~sl5~~sl4(-0.~~803~~68)	~~bldfie~~cecsol_sl1~~(-~~(0.~~787~~629)
orcdrc_~~sl5~~sl1	~~bldfie_sl4~~phihox_sl2(-0.~~759~~599)	~~bldfie_sl2~~phihox_sl3(-0.~~754~~594)	~~bldfie_sl5~~phihox_sl4(-0.~~745~~591)	~~bldfie_sl1~~phihox_sl5(-0.~~745~~586)	~~bldfie_sl3~~phihox_sl6(-0.~~731~~585)
~~orcdrc_sl6~~phihox_sl7	woody_savanna(-~~cecsol_sl2(~~0.~~733~~628)	~~bldfie_sl4~~pre_mean(-0.~~733~~598)	~~bldfie_sl2(-~~aridity(0.~~728~~592)	~~bldfie_sl1(-~~low_prec_freq(0.~~725~~588)	orcdrc_sl1~~bldfie_sl5~~(-0.~~721~~583)
phihox_sl6~~orcdrc_sl2~~	~~bldfie_sl2~~woody_savanna(-0.~~917~~627)	~~bldfie_sl1~~pre_mean(-0.~~908~~594)	~~bldfie_sl3(-~~aridity(0.~~861~~59)	~~cecsol_sl1(~~lai_max(-0.~~854~~587)	~~bldfie_sl4~~orcdrc_sl1(-0.~~854~~585)
phihox_sl5~~orcdrc_sl1~~	~~phihox_sl2~~woody_savanna(-0.~~826~~626)	~~phihox_sl1~~lai_max(-0.~~824~~593)	~~phihox_sl3~~pre_mean(-0.~~822~~592)	~~phihox_sl4(-~~aridity(0.~~819~~589)	~~phihox_sl5~~orcdrc_sl1(-0.~~813~~586)
phihox_~~sl7~~sl4	~~low_prec_freq(~~woody_savanna(-0.~~825~~628)	~~pre_mean~~lai_max(-0.~~819~~599)	~~lai_max~~orcdrc_sl1(-0.~~806~~591)	~~orcdrc_sl1~~lai_dif(-0.~~804~~578)	~~lai_dif~~pre_mean(-0.~~799~~576)
phihox_~~sl6~~sl3	~~low_prec_freq(~~woody_savanna(-0.~~818~~627)	lai_max(-0.~~814~~595)	~~pre_mean~~orcdrc_sl1(-0.~~81~~594)	~~orcdrc_sl1~~lai_dif(-0.~~807~~576)	~~lai_dif~~pre_mean(-0.~~807~~568)
phihox_~~sl5~~sl2	~~lai_max~~woody_savanna(-0.~~814~~627)	~~low_prec_freq(~~lai_max(-0.~~814~~602)	orcdrc_sl1(-0.~~813~~599)	lai_dif(-0.~~807~~583)	~~pre_mean(-~~low_prec_freq(0.~~801~~569)

phihox_~~sl4~~sl1	~~orcdrc_sl1~~woody_savanna(-0.~~819~~601)	lai_max(-0.~~815~~586)	~~lai_dif~~orcdrc_sl1(-0.~~809~~584)	~~low_prec_freq(~~lai_dif(-0.~~804~~565)	~~pre_mean(-~~bldfie_sl2(0.~~781~~55)
~~phihox_sl3~~bldfie_sl7	orcdrc_~~sl1~~sl5(-0.~~822~~547)	~~lai_max~~orcdrc_sl4(-0.~~813~~546)	~~lai_dif~~orcdrc_sl3(-0.~~806~~543)	orcdrc_sl6(-~~low_prec_freq(~~0.~~799~~534)	~~pre_mean~~orcdrc_sl7(-0.~~772~~523)
~~phihox_sl2~~bldfie_sl6	orcdrc_~~sl1~~sl5(-0.~~826~~559)	~~lai_max~~orcdrc_sl6(-0.~~813~~556)	~~lai_dif~~orcdrc_sl4(-0.~~807~~553)	~~low_prec_freq(~~orcdrc_sl7(-0.~~798~~548)	~~pre_mean~~orcdrc_sl3(-0.~~767~~547)
bldfie_sl5~~phihox_sl1~~	orcdrc_~~sl1~~sl3(-0.~~824~~621)	~~lai_max~~orcdrc_sl4(-0.~~804~~614)	~~lai_dif~~orcdrc_sl5(-0.~~798~~6)	~~low_prec_freq(~~orcdrc_sl2(-0.~~78~~597)	~~pre_mean~~orcdrc_sl7(-0.~~741~~572)
bldfie_~~sl7~~sl4	orcdrc_sl3(-0.~~775~~691)	orcdrc_~~sl4~~sl2(-0.~~747~~68)	orcdrc_~~sl5~~sl4(-0.~~698~~676)	orcdrc_~~sl2~~sl5(-0.~~698~~641)	orcdrc_sl6(-0.~~671~~584)
bldfie_~~sl6~~sl1	orcdrc_~~sl3~~sl2(-0.~~776~~769)	orcdrc_~~sl4~~sl3(-0.~~748~~701)	~~orcdrc_sl5~~cecsol_sl1(-0.~~701~~686)	orcdrc_~~sl2~~sl4(-0.~~694~~657)	~~orcdrc_sl6~~som(-0.~~677~~606)
bldfie_~~sl5~~sl3	orcdrc_~~sl3~~sl2(-0.~~849~~749)	orcdrc_~~sl2~~sl3(-0.~~81~~738)	orcdrc_sl4(-0.~~803~~702)	orcdrc_sl5(-0.~~745~~636)	~~orcdrc_sl7~~som(-0.~~728~~633)
bldfie_~~sl4~~sl2	orcdrc_~~sl3~~sl2(-0.~~875~~787)	orcdrc_~~sl2~~sl3(-0.~~854~~728)	orcdrc_sl4(-0.~~823~~682)	cecsol_sl1(-0.~~763~~671)	~~orcdrc_sl5~~som(-0.~~759~~651)
~~bldfie~~cecsol_sl1	~~orcdrc_sl2~~bldfie_sl1(-0.~~908~~686)	~~cecsol_sl1~~bldfie_sl2(-0.~~891~~671)	orcdrc_~~sl3(-~~sl2(0.~~848~~629)	~~cecsol_sl2~~bldfie_sl3(-0.~~828~~598)	orcdrc_~~sl4(-~~sl3(0.~~787~~579)
cecsol_sl2~~bldfie_sl3~~	~~orcdrc_sl3~~bldfie_sl1(-0.~~874~~579)	~~orcdrc~~bldfie_sl2(-0.~~861~~566)	orcdrc_~~sl4(-~~sl2(0.~~803~~553)	~~cecsol_sl1(-~~orcdrc_sl3(0.~~795~~523)	~~som~~bldfie_sl3(-0.~~787~~515)
~~bldfie_sl2~~cecsol_sl5	~~orcdrc_sl2~~bldfie_sl1(-0.~~917~~445)	~~orcdrc_sl3~~bldfie_sl2(-0.~~876~~429)	~~cecsol_sl1(-~~orcdrc_sl2(0.~~87~~412)	orcdrc_~~sl4(-~~sl3(0.~~809~~393)	~~som~~pet_mean(-0.~~808~~392)
cecsol_~~sl1~~sl4	bldfie_sl1(-0.~~891~~472)	bldfie_sl2(-0.~~87~~459)	orcdrc_sl2(0.~~854~~447)	~~bldfie~~orcdrc_sl3~~(-~~(0.~~795~~43)	orcdrc_~~sl3~~sl5(0.~~781~~424)
cecsol_~~sl2~~sl3	bldfie_sl1(-0.~~828~~532)	~~orcdrc~~bldfie_sl2~~(~~(-0.~~822~~52)	~~bldfie~~orcdrc_sl2~~(-~~(0.~~798~~508)	orcdrc_~~sl7~~sl3(0.~~758~~49)	orcdrc_~~sl3~~sl4(0.~~746~~478)
cecsol_~~sl5~~sl7	bldfie_sl1(-0.~~681~~413)	~~orcdrc~~bldfie_sl2~~(~~(-0.~~664~~396)	orcdrc_~~sl7~~sl2(0.~~649~~38)	~~bldfie_sl2~~pet_mean(-0.~~645~~374)	orcdrc_~~sl6~~sl3(0.~~636~~362)
cecsol_~~sl4~~sl6	bldfie_sl1(-0.~~72~~409)	~~orcdrc~~bldfie_sl2~~(~~(-0.~~717~~393)	orcdrc_~~sl7~~sl2(0.~~693~~378)	~~bldfie_sl2~~pet_mean(-0.~~692~~373)	orcdrc_~~sl6~~sl3(0.~~679~~36)

~~ecesol_sl3~~bdticm	~~bldfie_sl1(~~su(0.~~78~~452)	~~orcdrc_sl2(~~woody_savanna(-0.~~776~~412)	~~bldfie_sl2(~~low_prec_freq(0.~~76~~382)	~~orcdrc~~phihox_sl7(0.~~735~~378)	~~orcdrc_sl3(~~mixed_forest(-0.~~733~~374)
~~ecesol_sl7~~pdep	~~bldfie_sl1(~~theta_s_l4(0.~~661~~463)	~~orcdrc_sl7(~~elev(-0.~~654~~436)	~~orcdrc_sl2(~~grav(-0.~~642~~424)	~~orcdrc_sl6~~theta_s_l3(0.~~64~~42)	~~orcdrc_sl5~~lon(0.~~619~~4)
~~ecesol_sl6~~por	~~bldfie_sl1(~~som(0.~~648~~363)	~~orcdrc_sl2(~~bldfie_sl1(-0.~~637~~335)	~~orcdrc_sl7(~~phihox_sl1(-0.~~632~~329)	~~orcdrc_sl6(~~phihox_sl3(-0.~~62~~328)	~~bldfie~~phihox_sl2(-0.~~61~~328)
clay~~bdticm~~	~~su(~~sand(-0.~~599~~67)	~~low_prec_freq(~~log_k_s_l4(-0.~~463~~603)	log_k_s_~~l6(~~l3(-0.~~439~~592)	~~phihox_sl2(~~log_k_s_l1(-0.~~437~~59)	~~phihox_sl7(~~log_k_s_l2(-0.~~436~~578)
sand~~pdep~~	~~elev(~~log_k_s_l1(0.~~662~~71)	~~theta~~log_k_s_~~l4~~l2(0.~~571~~709)	~~e_min~~log_k_s_l3(0.~~566~~682)	~~lon(~~clay(-0.~~565~~67)	~~e_max~~log_k_s_l4(0.~~564~~612)
silt~~por~~	~~silt(~~sand(-0.573)	log_k_s_l1(-~~clay(~~0.~~366~~436)	~~tksatu~~log_k_s_l2(-0.~~317~~433)	~~som(~~log_k_s_l3(-0.~~3~~144)	~~tksatu_l1~~log_k_s_l4(-0.~~309~~316)
~~clay~~grav	~~pre_mean(~~theta_s_l2(-0.~~763~~585)	~~log_k~~theta_s_~~l4~~l1(-0.~~752~~582)	~~log_k~~theta_s_~~l1~~l3(-0.~~733~~522)	~~log_k~~theta_s_~~l2~~l4(-0.~~729~~515)	~~log_k~~theta_s_~~l3~~l5(-0.~~728~~433)
~~sand~~som	~~log_k_s_l2(~~bldfie_sl2(-0.~~86~~651)	~~log_k_s_l3(~~bldfie_sl3(-0.~~859~~633)	~~log_k_s_l1(~~bldfie_sl1(-0.~~858~~606)	~~log_k_s_l4~~orcdrc_sl2(0.~~82~~599)	~~log_k_s_l5~~orcdrc_sl3(0.~~773~~576)
~~silt~~high_prec_freq	~~por(~~root_depth_50(-0.~~573~~196)	~~sand(~~grassland(0.~~558~~175)	~~log_k_s_l3~~root_depth_99(-0.~~557~~171)	~~log_k_s_l2(~~som(0.~~547~~136)	~~log_k_s~~tksatu_l1(-0.~~545~~133)
high_prec_dur~~grav~~	theta_s_~~l2~~l6(-0.~~713~~277)	theta_s_~~l1~~l5(-0.~~705~~234)	~~theta_s_l4(~~p_seasonality(0.~~663~~233)	~~theta_s_l3(~~elev(0.~~662~~211)	theta_s_~~l5~~l4(-0.~~584~~201)
low_prec_freq~~som~~	~~bldfie_sl2~~pre_mean(-0.~~808~~766)	~~bldfie_sl3(~~aridity(0.~~787~~745)	~~bldfie_sl1(~~ssd_mean(0.~~759~~652)	~~bldfie_sl4~~rhu_mean(-0.~~747~~627)	~~orcdrc_sl2~~phihox_sl7(0.~~74~~588)

Appendix C: Data sources and data processing

The program to generate the data set is mainly written in Python. The rasterio[13] library is used to extract from the raster for the given basin boundary, reproject and merge rasters; The shapely[14] library is used to calculate the geometry; The pyproj[15] library is used for coordinate system conversions; The richdem[16] library is used to calculate slope; The netCDF4[17] and xarray[18] library is used to read the netCDF files; The pyshp[19] library is used to handle shapefiles; The gdal[20] command-line programs are used for data format conversions; The Python multiprocessing[21] library is used for multi-threaded data processing such as the calculation of meteorological time series; The interpolation program is written based on SciPy and NumPy. In addition, the calculation of the catchment boundary uses ArcPy[22]. However, ArcPy is not open sourced. The SURF_CLI_CHN_MUL_DAY dataset can be downloaded from https://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_DAY.html. It is freely available to global researchers but registration is required. The GDBD dataset can be downloaded at https://www.cger.nies.go.jp/db/gdbd/gdbd_index_e.html. ASTER GDEM dataset can be downloaded at: https://asterweb.jpl.nasa.gov/gdem.asp. GLHYMPS dataset can be downloaded at: https://dataverse.scholarsportal.info/dataset.xhtml?persistentId=doi:10.5683/SP2/DLGXYO; MODIS MCD12Q1 can be obtained from: https://lpdaac.usgs.gov/products/mcd12q1v006/; MODIS MCD15A3 can be obtained from: https://lpdaac.usgs.gov/products/mcd15a3hv006/; Soil hydraulic and thermal properties can be downloaded after registration: http://globalchange.bnu.edu.cn/research/soil5.jsp; Soil properties data can be downloaded after registration: http://globalchange.bnu.edu.cn/research/soil2; SoilGrids250m data download links: https://files.isric.org/soilgrids/former/2017-03-10/data/ with a list of descriptions: https://github.com/ISRICWorldSoil/SoilGrids250m/blob/master/grids/models/META_GEOTIFF_1B.csv.

Appendix D: Basin boundaries

This section briefly introduces how the basin boundaries are derived. The basin boundaries data used in this research are obtained from the GBDB (Masutomi, Inui et al. 2009) dataset. The GDBD dataset first distinguishing sinks caused by DEM

[13] https://rasterio.readthedocs.io/en/latest/

[14] https://shapely.readthedocs.io/en/stable/manual.html

[15] https://pyproj4.github.io/pyproj/stable/

[16] https://richdem.readthedocs.io/en/latest/

[17] https://unidata.github.io/netcdf4-python/

[18] http://xarray.pydata.org/en/stable/

[19] https://pypi.org/project/pyshp/

[20] https://gdal.org/api/python.html

[21] https://docs.python.org/3/library/multiprocessing.html

[22] https://pro.arcgis.com/zh-cn/pro-app/latest/arcpy/get-started/what-is-arcpy-.htm

errors, then the stream burning (Maidment 1996), and ridge fencing methods are used to modify the seeded DEM, then basin boundaries are produced with standardized procedures (Jenson, Domingue et al. 1988, Maidment and Morehouse 2002). Then the gauging station data from the GRDC (Center 2005) dataset is used to calibrate the derived basin boundaries. The derived basin areas were compared with the observed basin areas, and they showed a high degree of consistency with the observed basin data.

Appendix E: Guidelines for generating basin attributes for any basin

The published code[23] supports the automation of the calculation of the attributes for any given river basin and the generation of statistics files. In general, the user only needs to prepare the source data and ensure that the code environment is installed correctly, and then the user can run the code to calculate all attributes for the given river basin. The following describes the steps to generate data for any given watershed.

Prepare source data

In this step, the user needs to download the source data and place it in the corresponding location (Table D1). The code supports the calculation of meteorological time series based on the SURF_CLI_CHN_MUL_DAY data set. If the basin the user need to calculate is not in China, then the user needs to format the collected meteorological time series into the same format as the time series generated by the code. A sample file is available in the GitHub library.

Table D1: Instructions for preparing data sources

Data source	Download link	Example	Note
ASTER GDEM	https://search.earthdata.nasa.gov/search/ https://www.jspacesystems.or.jp/ersdac/GDEM/E/	./data/dems/ *.tif	
GLHYMPS	https://dataverse.scholarsportal.info/dataset.xhtml?persistentId=doi:10.5683/SP2/DLGXYO (using source data requires merging multiple small pieces to a single TIFF)	./data/processed_permeability.tif ./data/processed_porosity.tif	

[23] https://github.com/haozhen315/CCAM-China-Catchment-Attributes-and-Meteorology-dataset

	https://1drv.ms/u/s!AqzR0fLyn9KKspF6HAAuXU9Twkkz1Q?e=QCPFAm (our processed file) https://1drv.ms/u/s!AqzR0fLyn9KKspF70EPmDubS5V2qTQ?e=Rbybwa (our processed file)		
GLiM	https://csdms.colorado.edu/wiki/Data:GLiM https://1drv.ms/u/s!AqzR0fLyn9KKspF5Vktb-zlmd_Ctxg?e=G6fOuh (our processed file)	./data/processed_glim.py	
MCD12Q1	https://lpdaac.usgs.gov/products/mcd12q1v006/ https://1drv.ms/u/s!AqzR0fLyn9KKspF4xxbe0xM7qJNzkA?e=vyFcFj (our processed file)	./data/processed_igbp.tif	
MCD15A3	https://lpdaac.usgs.gov/products/mcd15a3hv006/	./data/MCD15A3/MCD15A3H.A2002185.h22v04.006.2015149102803.hdf	
MOD13Q1	https://lpdaac.usgs.gov/products/mod13q1v006/	./data/MOD13Q1/MOD13Q1.A2002186.h22v04.006.2015149102803.hdf	
Soil	http://globalchange.bnu.edu.cn/research/soil5.jsp	./data/soil_souce_data/binary/log_k_s_l1	
Soil	https://files.isric.org/soilgrids/former/2017-03-10/data/	./data/soil_souce_data/tif/BDTICM_M_250m_ll.tif	Description: https://github.com/ISRICWorldSoil/SoilGrids250m/blob/master/grids/models/META_GEOTIFF_1B.csv
Soil	http://globalchange.bnu.edu.cn/research/soil2	./data/soil_souce_data/tif/SA.nc	

SURF_CLI_CHN_MUL_DAY	https://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_DAY.html	./data/SURF_CLI_CHN_MUL_DAY/Data/EVP/SURF_CLI_CHN_MUL_DAY-EVP-13240-195101.TXT	If basin boundary is outside China, format and place the collected time series data in ./output/catchment_meteorological
Root depth	https://github.com/haozhen315/CCAM-China-Catchment-Attributes-and-Meteorology-dataset/blob/main/data/root_depth_calculated.txt	./data/root_depth_calculated.txt	Calculated root depth of each land type according to (Zeng 2001).
GLiM name mapping	https://github.com/haozhen315/CCAM-China-Catchment-Attributes-and-Meteorology-dataset/blob/main/data/glim_name_short_long.txt https://github.com/haozhen315/CCAM-China-Catchment-Attributes-and-Meteorology-dataset/blob/main/data/glim_cate_number_mapping.csv	./data/glim_cate_number_mapping.csv ./data/glim_name_short_long.txt	These files are used for name conversions in the program.
GDBD	https://www.cger.nies.go.jp/db/gdbd/gdbd_index_e.html	./data/river_network/as_streams_wgs.shp	River network shapefiles are used to determine river basin shape factors. The source data need to be reprojected to EPSG:4326 (using ArcMap or QGIS) to successfully run the code. Note that files in different regions have different names.

Run the code

When all the data is ready, the user can run the code calculate_all_attributes.py to calculate all attributes or run separate scripts (e.g., soil.py) to calculate indicators for specific categories. The result will appear in the output folder.

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