SYNERGY BETWEEN SATELLITE OBSERVATIONS OF SOIL MOISTURE AND WATER STORAGE ANOMALIES FOR RUNOFF ESTIMATION

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November 2020

Submitted to:

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ABSTRACT

This paper presents an innovative approach, STREAM - SaTellite based Runoff Evaluation And Mapping - to derive daily river discharge and runoff estimates from satellite soil moisture, precipitation and terrestrial water storage anomalies observations. Within a very simple model structure, the first two variables (precipitation and soil moisture) are used to estimate the quick-flow river discharge component while the terrestrial water storage anomalies are used for obtaining its complementary part, i.e., the slow-flow river discharge component. The two are then summed up to obtain river discharge and runoff estimates.

The method is tested over the Mississippi river basin for the period 2003-2016 by using Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) precipitation data, European Space Agency Climate Change Initiative (ESA CCI) soil moisture data and Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage data. Despite the model simplicity, relatively high-performance scores are obtained in river discharge simulations, with a Kling-Gupta efficiency index greater than 0.65 both at the outlet and over several inner stations used for model calibration highlighting the high information content of satellite observations on surface processes. Potentially useful for multiple operational and scientific applications (from flood warning systems to the understanding of water cycle), the added-value of the STREAM approach is twofold: 1) a simple modelling framework, potentially suitable for global runoff monitoring, at daily time scale when forced with satellite observations only, 2) increased knowledge on the natural processes, human activities and on their interactions on the land.

Key words: satellite products, soil moisture, water storage variations, conceptual hydrological modelling, rainfall-runoff modelling, Mississippi.

1. INTRODUCTION

Spatial and temporal continuous river discharge monitoring is paramount for improving the understanding of the hydrological cycle, for planning human activities related to water use as well as to prevent/mitigate the losses due to extreme flood events. To accomplish these tasks, runoff and river discharge data, which represents the aggregated signal of runoff (Fekete et al., 2012), should be available at adequate spatial/temporal resolution, i.e., at basin scale (basin area larger than 10’000 km^2) and at monthly time step for water resources management and drought monitoring up to grid scale (few km)/(sub-) daily time step for flood prediction. The accurate continuous (in space and time) runoff and river discharge estimation at finer spatial/temporal resolution is still a big challenge for hydrologists.

Traditional in situ observations of river discharge, even if generally characterized by high temporal resolution (up to sub-hourly time step), typically offer little information on the spatial distribution of runoff within a watershed. Moreover, river discharge observation networks suffer from many limitations such as low station density and often incomplete temporal coverage, substantial delay in data access and large decline in monitoring capacity (Vörösmarty et al. 2002). Paradoxically, this latter issue is exacerbated in developing nations (Crochemore et al, 2020), where the knowledge of the terrestrial water dynamics deserves greater attention due to huge damages to settlements and especially the loss of human lives that occurs regularly.

This precarious situation has led to growing interest in finding alternative solutions, i.e., model-based or observation-based approaches, for runoff and river discharge monitoring. Model-based approaches, based on the mathematical description of the main hydrological processes (e.g., water balance models, WBMs, global hydrological models, GHMs, e.g., Döll et al., 2003 or, increasing in complexity, land surface models, LSM, e.g., Balsamo et al., 2009; Schellekens et al., 2017), are able to provide comprehensive information on a large number of relevant variables of the hydrological cycle including runoff and river discharge at very high temporal and spatial resolution (up to hourly sampling and 0.05° grid scale). However, the values of simulated water balance components rely on a massive parameterization of the soil, vegetation and land parameters, which is not always realistic, and are strongly dependent on the GHM/ LSM models used, analysis periods (Wisser et al., 2010) and climate forcings selected (e.g Haddeland et al., 2012; Gudmundsson et al., 2012a, b; Prudhomme et al., 2014; Müller Schmied et al., 2016).

Alternatively, the observation-based approaches exploit machine learning techniques and a considerable amount of data to describe the physics of the system (i.e. hydraulic and/or hydrologic phenomena, Solomatine and Ostfeld, 2008) with only a limited number of assumptions. Besides being simpler than model-based approaches, these approaches still present some limitations. At first, as they rely on a considerable amount of data describing the modelled system's physics, the spatial/temporal extent and the uncertainty of the resulting dataset is determined by the spatial/temporal coverage and the accuracy of the forcing data (e.g., see E-RUN dataset, Gudmundsson and Seneviratne, 2016; GRUN dataset, Ghiggi et al., 2019; FLO1K dataset, Barbarossa et al., 2018). Additional limitations stem from the employed method to estimate runoff. Indeed, random forests such as employed in Gudmundsson and Seneviratne, 2016, like other machine learning techniques, are powerful tools for data driven modeling, but they are prone to overfitting, implying that noise in the data can obscure possible signals (Hastie et al., 2009). Moreover, the influence of land parameters on continental-scale runoff dynamics is not taken into account as the underlying hypothesis is that the hydrological response of a basin exclusively depend on present and past atmospheric forcing. It is easy to understand that this assumption will only be valid in certain circumstances and might lead to problems, e.g., over complex terrain (Orth and Seneviratne, 2015) or in cases of human river flow regulation (Ghiggi et al., 2019).

Remote sensing can provide estimates of nearly all the climate variables of the global hydrological cycle including soil moisture (e.g., Wagner et al., 2007; Seneviratne et al., 2010), precipitation (Huffman et al., 2014) and total terrestrial water storage (e.g., Houborg et al., 2012; Landerer and Swenson, 2012; Famiglietti and Rodell, 2013). It has undeniably changed and improved dramatically the ability to monitor the global water cycle and, hence, runoff. By taking advantage of satellite information, some studies tried to develop methodologies able to optimally produce multivariable datasets from the fusion of in situ and satellite-based observations (e.g., Rodell et al., 2015; Zhang et al., 2018; Pellet et al., 2019). Other studies exploited satellite observations of hydrological variables, e.g., precipitation (Hong et al, 2007), soil moisture (Massari et al., 2014), and geodetic variables (e.g., Sneeuw at. al., 2014; Tourian et al., 2018) to monitor single components of the water cycle in an independent way.

Although the majority of these studies provide runoff and river discharge data at basin scale and monthly time step, they deserve to be recalled here as important for the purpose of the present study. In particular, Hong et al. (2007) presented a first attempt to obtain an approximate but quasi-global annual streamflow dataset, by incorporating satellite precipitation data in a relatively simple rainfall-runoff simulation approach. Driven by the multiyear (1998-2006) Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis, runoff was independently computed for each global land surface grid cell through the Natural Resources Conservation Service (NRCS) runoff curve number (CN) method (NRCS, 1986) and subsequently routed to the watershed outlet to simulate streamflow. The results, compared to the in situ observed discharge data, demonstrated the potential of using satellite precipitation data for diagnosing river discharge values both at global scale and for medium to large river basins. If, on the one hand, the work of Hong et al. (2007) can be considered as a pioneer study, on the other hand it presents a serious drawback within the NRCS-CN method that lacks a realistic definition of the soil moisture conditions of the catchment before flood events. This aspect is not negligible, as it is well established that soil moisture is paramount in the partitioning of precipitation into surface runoff and infiltration inside a catchment (Brocca et al., 2008). In particular, for the same rainfall amount but different values of initial soil moisture conditions, different flooding effects can occur (see e.g. Crow et al., 2005; Brocca et al., 2008; Berthet et al., 2009; Merz and Bloschl, 2009; Tramblay et al., 2010). On this line following Brocca et al. (2009), Massari et al. (2016) presented a very first attempt to estimate global streamflow data by using satellite Soil Moisture Active and Passive (SMAP, Entekhabi et al.., 2010) and Global Precipitation Measurement (GPM, Huffman et al., 2019) products. Although the validation was carried out by routing the monthly surface runoff only in a single basin in Central Italy, the obtained results suggested to dedicate additional efforts in this direction.

Among the studies that use satellite observations of hydrological variables for runoff estimation, the hydro-geodetic approaches are undoubtedly worth mentioning, see e.g., Sneeuw et al.,2014 for a comprehensive overview or Lorenz et al. (2014) for an analysis of satellite-based water balance misclosures with discharge as closure term. In particular, the satellite mission Gravity Recovery And Climate Experiment (GRACE), which observed the temporal changes in the gravity field, has given a strong impetus to satellite-driven hydrology research (Tapley et al., 2019). Since temporal gravity field variations over the continents imply water storage change, GRACE was the first remote sensing system to provide observational access to deeper groundwater storage. The relation between GRACE groundwater storage change and runoff was characterized by Riegger and Tourian (2014), which even allowed the quantification of absolute drainable water storage over the Amazon (Tourian et al., 2018). In essence the storage-runoff relation describes the gravity-driven drainage of a basin and, hence, the slow-flow processes. Due to GRACE's spatial-temporal resolution, runoff and river discharge are generally available for large basins (>160'000 km^2) and at monthly time step.

Based on the above discussion, it is clear that each approach presents strengths and limitations that enable or hamper the runoff and river discharge monitoring at finer spatial and temporal resolutions. In this context, this study presents an attempt to find an alternative method to derive daily river discharge and runoff estimates at ¼ degree spatial resolution exploiting satellite observations and the knowledge of the key mechanisms and processes that act in the formation of runoff, i.e., the role of soil moisture in determining the response of a catchment to precipitation. For that, soil moisture, precipitation and terrestrial water storage anomalies (TWSA) observations are used as input into a simple modelling framework named STREAM v1.3 (SaTellite based Runoff Evaluation And Mapping, version 1.3). Unlike classical land surface models, STREAM exploits the knowledge of the system states (i.e., soil moisture and TWSA) to derive river discharge and runoff, and thus it 1) skips the modelling of the evapotranspiration fluxes which are known to be a non-negligible source of uncertainty (Long et al. 2014), 2) limits the uncertainty associated with the over-parameterization of soil and land parameters and 3) implicitly takes into account processes, mainly human-driven (e.g., irrigation, change in the land use), that might have a large impact on the hydrological cycle and hence on runoff.

The detailed description of the STREAM v1.3 model is given in section 4. The collected datasets and the experimental design for the Mississippi River Basin (section 2) are described in sections 3 and 5, respectively. Results, discussion and conclusions are drawn in section 6, 7 and 8, respectively.

2. STUDY AREA

The STREAM v1.3 model presented here has been tested and validated over the Mississippi River basin. With a drainage area of about 3.3 million km2, the Mississippi River basin is the fourth largest watershed in the world, bordered to the West by the crest of the Rocky Mountains and to the East by the crest of the Appalachian Mountains. According to the Köppen climate classification, the climate is subtropical humid over the southern part of the basin, continental humid with hot summer over the central part, continental humid with warm summer over the eastern and northern parts, whereas a semiarid cold climate affects the western part. The average annual air temperature across the watershed ranges from 4°C in the West to 6°C in the East. On average, the watershed receives about 900 mm/year of precipitation (77% as rainfall and 23% as snowfall), more concentrated in the eastern and southern portions of the basin with respect to its northern and western part (Vose et al., 2014).

The river flow has a clear natural seasonality mainly controlled by spring snowmelt (coming from the Missouri and the Upper Mississippi, the eastern and the upper part of the basin, respectively, Dyer 2008) and by heavy precipitation exceeding the soil moisture storage capacity (mostly occurring in the eastern and southern part of the basin, Berghuijs et al., 2016). The basin is also heavily regulated by the presence of large dams (Global Reservoir and Dam Database GRanD, Lehner et al., 2011) most of them located on the Missouri river, over the Great Plains. In particular, the river reach between Garrison and Gavins Point dams is the portion of the Missouri river where the large main-channel dams have the greatest impact on river discharge providing a substantial reduction in the annual peak floods, an increase on low flows and a reduction on the overall variability of intra-annual discharges (Alexander et al., 2012). The annual average of Mississippi river discharge at the Vicksburg outlet section is equal to 17'500 m^3/s (see Table 1). Given the variety of climate and topography across the Mississippi River basin, it is a good candidate to test the suitability of the STREAM v1.3 model for river discharge and runoff simulation.

3. DATASETS

The datasets used in this study include in situ observations, satellite products and model outputs. The first two datasets have been used as input data to the STREAM v1.3 model. Conversely, the model outputs are used as a benchmark to validate the performance of the STREAM v1.3 model.

3.1 In situ Observations

In situ observations comprise air temperature (T_{air}) and river discharge data (Q).

For T_{air} data the Climate Prediction Center (CPC) Global Temperature data developed by the American National Oceanic and Atmospheric Administration (NOAA) using the optimal interpolation of quality-controlled gauge records of the Global Telecommunication System (GTS) network (Fan et al., 2008) have been used. The dataset, downloadable at (https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html) is available on a global regular 0.5°×0.5° grid, and provides daily maximum (T_{max}) and minimum (T_{min}) air temperature data from 1979 to present. The daily average air temperature data have been generated as the mean of T_{max} and T_{min} of each day.

Daily Q data over the study basins have been taken from the Global Runoff Data Center (GRDC, https://www.bafg.de/GRDC/EN/Home/homepage_node.html). In particular, 11 gauging stations located along the main river network of the Mississippi River basin have been selected to represent the spatial distribution of runoff over the basin. The location of these gauging stations along with relevant characteristics (e.g., the upstream basin area, the mean annual river discharge and the presence of upstream dams) are summarized in Table 1. As it can be noted, mean annual river discharge ranges from 141 to 17’500 m3/s, and 3 out 11 sections are located downstream big dams (Lehner et al., 2011). In particular, Garrison (the fifth-largest earthen dam in the world), Gavins Point and Kanopolis dams located downstream section 1, 2 and 5 respectively (see Figure 3 and Table 1), are three large dams with a maximum storage of 29’383×10^9 m^3, 0.607×10^9 m^3, and 1.058×10^9 m^3 respectively.

3.2 Satellite Products

Satellite products include observations of precipitation (*P*), soil moisture and TWSA.

The satellite *P* dataset used in this study is the Multi-satellite Precipitation Analysis 3B42 Version 7 (TMPA 3B42 V7) estimate produced by the National Aeronautics and Space Administration (NASA) as the 0.25°×0.25° quasi-global (50°N-S) gridded dataset. The TMPA 3B42 V7 is a gauged-corrected satellite product, with a latency period of two months after the end of the month of record, available at 3h sampling interval from 1998 to present (2020). Major details about the *P* dataset, downloadable from http://pmm.nasa.gov/data-access/downloads/trmm, can be found in Huffman et al. (2007).

Soil moisture data have been taken from the European Space Agency Climate Change Initiative (ESA CCI) Soil Moisture project (https://esa-soilmoisture-cci.org/) that provides a surface soil moisture product (referred to first 2-3 centimeters of soil) continuously updated in term of spatial-temporal coverage, sensors and retrieval algorithms (Dorigo et al., 2017). In this study, the daily combined ESA CCI soil moisture product v4.2 is used, that is available at global scale with a grid spacing of 0.25°, for the period 1978-2016.

TWSA have been obtained from the Gravity Recovery And Climate Experiment (GRACE) satellite mission. Here we employ the NASA Goddard Space Flight Center (GSFC) global mascon model, i.e., Release v02.4, (Luthcke et al. 2013). It has been produced based on the mass concentration (mascon) approach. The model provides surface mass densities on a monthly basis. Each monthly solution represents the average of surface mass densities within the month, referenced at the middle of the corresponding month. The model has been developed directly from GRACE level-1b K-Band Ranging (KBR) data. It is computed and delivered as surface mass densities per patch over blocks of approximately 1°×1° or about 12’000 km^2. Although the mascon size is smaller than the inherent spatial resolution of GRACE, the model exhibits a relatively high spatial resolution. This is attributed to a statistically optimal Wiener filtering, which uses signal and noise full covariance matrices. This allows the filter to fine tune the smoothing in line with the signal-to-noise ratio in different areas. That is, the less smoothing, the higher signal-to-noise ratio in a particular area and vice versa. This ensures that the filtering is minimal and aggressive smoothing is avoided when unnecessary. Further details of such a filter can be found in Klees et. al (2008). Importantly, the coloured (frequency-dependent) noise characteristic of KBR data was taken in to account when compiling the GRACE model, which has allowed for a reliable computation of the aforementioned noise full covariance matrices. The coloured (frequency-dependent) noise characteristic of KBR data was taken into account when compiling the model, which has allowed for a reliable computation of these noise and signal covariance matrices. They play a crucial role when filtering and allow to achieve a higher spatial resolution compared to commonly applied GRACE filtering methods such as Gaussian smoothing and/or destriping filters. GRACE data are available for the period 01 January 2003 to 15 July 2016.

3.3 Model Outputs

To establish the quality of the STREAM v1.3 model in runoff simulation, monthly runoff (R) data obtained from the Global Runoff Reconstruction (GRUN_v1, https://doi.org/10.3929/ethz-b-000324386) have been used for comparison. The GRUN dataset (Ghiggi et al., 2019) is a global monthly R dataset derived through the use of a machine learning algorithm trained with in situ Q observations of relatively small catchments (<2500 km^2) and gridded precipitation and temperature derived from the Global Soil Wetness Project Phase 3 (GSWP3) dataset (Kim et al., 2017). The dataset covers the period from 1902 to 2014 and it is provided on a 0.5° ×0.5° regular grid.

4. METHOD

4.1 STREAM Model: the Concept

The concept behind the STREAM v1.3 model is that river discharge is a combination of hydrological responses operating at diverse time scales (Blöschl et al., 2013; Rakovec et al., 2016). In particular, river discharge can be considered made up of a *slow-flow component*, produced as outflow of the groundwater storage and of a *quick-flow component*, i.e. mainly related to the surface and subsurface runoff components (Hu and Li, 2018).

While the high spatial and temporal (i.e., intermittence) variability of precipitation and the highly changing land cover spatial distribution significantly impact the variability of the *quick-flow component* (with scales ranging from hours to days and meters to kilometres depending on the basin size), *slow-flow river discharge* reacts to precipitation inputs more slowly (i.e., months) as water infiltrates, is stored, mixed and is eventually released in times spanning from weeks to months. Therefore, the two components can be estimated by relying upon two different approaches that involve different types of observations. Based on that, within the STREAM v1.3 model, satellite soil moisture, precipitation and TWSA will be used for deriving river discharge and runoff estimates. The first two variables are used as proxy of the *quick-flow* river discharge component while TWSA is exploited for obtaining its complementary part, i.e., the *slow-flow river discharge* component. Firstly, we exploit the role of the soil moisture in determining the response of the catchment to the precipitation inputs, which have been soundly demonstrated in more than ten years of literature studies (see e.g., Brocca et al., 2017 for a comprehensive discussion on the topic). Secondly, we consider the important role of terrestrial water storage in determining the slow-flow river discharge component as modelled in several hydrological models (e.g., Sneeuw et al., 2014).

It is worth noting that this *modus operandi*, i.e. to model the *quick-flow* and *slow-flow* discharge component separately exploring their process controls independently, has been largely applied and tested in recent and past studies, e.g., for the estimation of the flow duration curve (see e.g, Botter et al., 2007a, b; Yokoo and Sivapalan 2011; Muneepeerakul et al., 2010; Ghotbi et al., 2020).

4.2 STREAM Model: the Laws

The STREAM v1.3 model is a conceptual hydrological model that, by using as input observation of P, soil moisture, TWSA and T_{air} data, simulates continuous R and Q time series.

The model entails three main components (Figure 1): 1) a snow module to separate precipitation into snowfall and rainfall, 2) a soil module to simulate the evolution in time t of the quick and slow runoff responses, Qfu [mm] and Qsl [mm], and 3) a routing module that transfers these components through the basins and the rivers for the simulation of the *quick-flow* river discharge, *QF* [m^3/s], and the *slow-flow* river discharge, *SF* [m^3/s] components. The soil module is composed of two storages, *Su* and *Sl* as illustrated in Figure 1. The upper storage receives inputs from P, released through a snow module (Cislaghi et al., 2020) as rainfall (r) or stored as snow water equivalent (*SWE*) within the snowpack and on the glaciers. In particular, according to Cislaghi et al. (2020), *SWE* is modelled by using as input T_{air} and a degree-day coefficient, C_{m}, to be estimated by calibration. We have to acknowledge that, even though this rain/snow differentiation method works quite efficiently at a large grid size like the one used in the study (25 x 25 km), the topographic complexity of higher elevations can be lost. A different differentiation scheme based e.g., on the wet bulb temperature like in IMERG (Wang et al., 2019; Arabzadeh and Behrangi, 2021), would be preferable but is out of the purpose study.

Once separated, r input contributes to the quick runoff response while the *SWE* (like other fluxes contributing to modify the soil water content into *Su*) is neglected as already considered in the satellite TWSA. Therefore, the first key point of the STREAM v1.3 model is that the water content in the upper storage is directly provided by the satellite soil moisture observations and the loss processes like infiltration or evaporation do not need to be explicitly modelled to simulate the evolution in time

t of soil moisture. Consequently, the quick runoff response, Qfu from the first storage can be computed following the formulation proposed by Georgakakos and Baumer (1996), as in equation (1):

$$Qfu(t) = r(t)\,SWI(t,T)^{\alpha} \qquad (1)$$

where:

- SWI is the Soil Water Index (Wagner et al., 1999), i.e., the root-zone soil moisture product referred to the first layer of the model (representative of the first 5-30 centimeters of soil), derived by the surface satellite soil moisture product, θ, by applying the exponential filtering approach in its recursive formulation (Albergel et al., 2009):

$$SWI_n = SWI_{n-1} + K_n(\theta(t_n) - SWI_{n-1}) \qquad (2)$$

with the gain K_n at the time t_n given by:

$$K_n = \frac{K_{n-1}}{K_{n-1} + e^{\left(\frac{t_n - t_{n-1}}{T}\right)}} \qquad (3)$$

- T [days] is a parameter, named characteristic time length, that characterizes the temporal variation of soil moisture within the root-zone profile and the gain K_n ranges between 0 and 1;
- α[-] is a coefficient linked to the non-linearity of the infiltration process and it takes into account the characteristics of the soil;
- for the initialization of the filter $K_1 = 1$ and $SWI_1 = \theta(t_1)$.

The second key point of STREAM v1.3 model concerns the estimation of the slow runoff response, Qsl, from the second storage. The hypothesis here, shared also with other studies (e.g., Rakovec et al., 2016), is that the dynamic of the slow runoff component can be represented by the monthly TWSA data. Indeed, the time scale of slow runoff response is typically in the range of seasons to years and it can be assumed almost independent upon the water that is contained in that upper storage. For that, the slow runoff response Qsl, from the second storage, can be computed following the formulation proposed by Famiglietti and Wood (1994), through equation (4) as follows:

$$Qsl(t) = \beta \left(TWSA^{*}(t)\right)^{m} \qquad (4)$$

where:

- $TWSA^{*}$ [-] is the TWSA estimated by GRACE normalized by its minimum and maximum values. The assumption behind this equation is that TWSA can be assumed as a proxy of the evolution in time, t, of the Sl, i.e., the storage of the lower storage.
- β [mm h^{-1}] and m [-] are two parameters describing the nonlinearity between slow runoff component and $TWSA^{*}$.

Note that we made the hypothesis that soil moisture and TWSA observations are independent (whereas in the reality soil moisture can be responsible both for the generation of the quick flow part (mainly) and for the slow flow contribution) given the different temporal (and spatial) scales at which the quick and slow runoff responses act.

The STREAM v1.3 model runs in a semi-distributed version in which the catchment is divided into *s* elements, each one representing either a subcatchment with outlet along the main channel or an area draining directly into the main channel. Each element is assumed homogeneous and hence constitutes a lumped system.

The routing module (controlled by a γ parameter) conveys the Qfu and Qsl response components at each element outlet (subcatchments and directly draining areas, Brocca et al., 2011) and successively at the catchment outlet of the basin. Specifically, the quick component Qfu is routed to the element outlet by the Geomorphological Instantaneous Unit Hydro-graph (GIUH, Gupta et al., 1980) for subcatchments or through a linear reservoir approach (Nash, 1957) for directly draining areas; the Qsl slow component is transferred to the outlet section by a linear reservoir approach. Finally, a diffusive linear approach (controlled by the parameters *C* and *D*, i.e., Celerity and Diffusivity, Troutman and Karlinger, 1985) is applied to route the quick and slow runoff components at the outlet section of the catchment (Brocca et al., 2011). In the first case we obtain the *quick-flow* river discharge component, *QF* [m^3/s], and in the second case the *slow-flow* river discharge component, *SF* [m^3/s] (see Figure 1).

4.3 STREAM Parameters

The STREAM v1.3 model uses 8 parameters of which 5 are used in the soil module (α, T [days], β [mm h^{-1}], m, Cm) and 3 in the routing module (γ, C [km h^{-1}] and D [km^2 h^{-1}]). The parameter values, determined within the feasible parameter space (See Table Appendix A for more details), are calibrated by maximizing the Kling-Gupta Efficiency index (KGE, Gupta et al., 2009; Kling et al., 2012, see paragraph 5.1 for more details) between observed and simulated river discharge. For model calibration, a standard gradient-based automatic optimisation method (Bober 2013) was used.

5. EXPERIMENTAL DESIGN

5.1 Modelling Setup for Mississippi River Basin

The modelling setup is carried out in three steps (Figure 2):

1. *Sub-basin delineation.* STREAM v1.3 model is run in the semi-distributed version over the Mississippi River basin. The TopoToolbox (https://topotoolbox.wordpress.com/), a tool developed in Matlab by Schwanghart et al. (2010), and the SHuttle Elevation Derivatives at multiple Scales (HydroSHED, https://www.hydrosheds.org/) DEM of the basin at the 3′′ resolution (nearly 90 m at the equator) have been used to derive flow directions, to extract the stream network and to delineate the drainage basins over the Mississippi River basin. In particular, by considering only rivers with order greater than 3 (according to the Horton-Strahler rules, Horton, 1945; Strahler, 1952), the Mississippi watershed has been divided into 53 sub-basins as illustrated in Figure 3. Red dots in the figure indicate the location of the 11 discharge gauging stations selected for the study area.

It has to be specified that the step of sub-basin delineation could be accomplished through tools different from the TopoToolbox. For instance, it could be used the free Qgis software downloadable at https://www.qgis.org/it/site/forusers/download.html, following the instruction to perform the hydrological analysis as in https://docs.qgis.org/3.16/en/docs/training_manual/processing/hydro.html?highlight=hydrological%20analysis.

2. *Extraction of input data.* Precipitation, T_{air}, soil moisture and TWSA datasets data have to be extracted for each sub-basin of the study area. If characterized by different spatial/temporal resolution, these datasets need to be resampled over a common spatial grid/temporal time step prior to be used as input into the model.

To run the STREAM v1.3 model over the Mississippi river basin, input data have been resampled over the precipitation spatial grid at 0.25° resolution through a bilinear interpolation. Concerning the temporal scale, T_{air}, soil moisture and precipitation data are available at daily time step, while monthly TWSA data have been linearly interpolated at daily time step. For each of the 53 Mississippi subbasins, the resampled precipitation, soil moisture, T_{air} and TWSA data have been extracted.

3. *STREAM model calibration.* In situ river discharge data are used as reference data for the calibration of STREAM v1.3 model. For Mississippi, the STREAM v1.3 model has been calibrated over five sections as illustrated in Figure 3: the inner sections 4, 6, 9, 11 and the outlet section 10, are used to calibrate the model and all sub-basins contributing to the respective sections are highlighted with the same colour. This means that, for example, the sub-basins labelled as 1, 2, 5 to 15, 17, 22, 23, and 30 contribute to section 4, sub-basins 31, 37, 38 and 41 contribute to section 6 and so on. Consequently, the sub-basins highlighted with the same colour are assigned the same model parameters, i.e. the parameters that allow to reproduce the river discharge data observed at the related outlet section.

Once calibrated, the STREAM v1.3 model has been run to provide continuous daily Q and R time series, at the outlet section of each subbasin and over each grid pixel, respectively. By considering the spatial/temporal availability of both in situ and satellite observations, the entire analysis period covers the maximum common observation period, i.e., from 01 January 2003 to 15 July 2016 at daily time scale. To establish the goodness-of-fit of the model, the simulated river discharge and runoff timeseries are compared against in situ river discharge and modelled runoff data.

5.2 Model Evaluation Criteria and Performance Metrics

The model has been run over a 13.5-year period split into two sub periods: the first 8 years, from January 2003 to December 2010, have been used to calibrate the model successively validated over the remaining 5.5 years (January 2011 - July 2016).

In particular, three different validation schemes have been adopted to assess the robustness of the STREAM v1.3 model:

1. Internal validation aimed to test the plausibility of both the model structure and the parameter set in providing reliable estimates of the hydrological variables against which the model is calibrated. For this purpose, a comparison between observed and simulated river discharge time series on the sections used for model calibration has been carried out for both the calibration and validation sub periods.
2. Cross-validation testing the goodness of the model structure and the calibrated model parameters to predict hydrological variables at locations not considered in the calibration phase. In this respect, the cross-validation has been carried out by comparing observed and simulated river discharge time series in gauged basins not considered during the calibration phase;
3. External validation aimed to test the capability of the model "*to get the right answers for the right reasons*" (Kirchner 2006). The rationale behind this concept is that the hydrological models are today highly performing and able to reproduce a lot of hydrological variables. For that, the model performances should not only be evaluated against observed streamflow, but complementary datasets representing internal hydrologic states and fluxes (e.g., soil moisture, evapotranspiration, runoff etc) should be considered. As runoff is a secondary product of the

STREAM v1.3 model, obtained indirectly from the calibration of the river discharge (basin-integrated runoff), the comparison in terms of runoff can be considered as a further external validation of the model. Runoff, differently from discharge, cannot be directly measured. It is generally modelled through land surface or hydrological models. Its validation requires a comparison against modelled data that, however, suffer from uncertainties (Beck et al., 2017). Based on that, in this study the GRUN runoff dataset described in the section 3.3 has been used for a qualitative comparison.

5.3 Performance Metrics

To measure the goodness-of-fit between simulated and observed river discharge data three performance scores have been used:

- the relative root mean square error, RRMSE:

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Qsim_i - Q_{obs_i}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}\left(Q_{obs_i}\right)} \quad (5)$$

where Q_{obs} and Q_{sim} are the observed and simulated discharge time series of length n. RRMSE values range from 0 to +∞, the lower the RRMSE, the better the agreement between observed and simulated data.

- the Pearson correlation coefficient, R, measures the linear relationship between two variables:

$$R = \frac{\sum_{i=1}^{n}\left(Qsim_i - \overline{Qsim_i}\right)\left(Qobs_i - \overline{Qobs_i}\right)}{\sqrt{\sum_{i=1}^{n}\left(Qsim_i - \overline{Qsim_i}\right)^2\left(Qobs_i - \overline{Qobs_i}\right)^2}} \quad (6)$$

where $\overline{Q_{obs}}$ and $\overline{Q_{sim}}$ represent the mean values of Q_{obs} and Q_{sim}, respectively. The values of R range between -1 and 1; higher values of R indicate a better agreement between observed and simulated data.

- the Kling-Gupta efficiency index (KGE, Gupta et al., 2009), which provides direct assessment of four aspects of discharge time series, namely shape, timing, water balance and variability. It is defined as follows:

$$KGE = 1 - \sqrt{(R-1)^2 + (\delta-1)^2 + (\varepsilon-1)^2} \quad (7)$$

where R is the correlation coefficient, δ the relative variability and ε the bias normalized by the standard deviation between observed and simulated discharge. The KGE values range between $-\infty$ and 1; the higher the KGE, the better the agreement between observed and simulated data. Simulations characterized by values of KGE in the range -0.41 and 1 can be assumed as reliable; values of KGE greater than 0.5 have been assumed good with respect to their ability to reproduce observed time series (Thiemig et al., 2013).

6. RESULTS

The testing and validation of the STREAM v1.3 model is presented and discussed in this section according to the scheme illustrated in section 5.2.

6.1 Internal Validation

The performance of the STREAM v1.3 model over the calibrated river sections is illustrated in Figure 4 and summarized in Table 2. Figure 4 shows observed and simulated river discharge time series over the whole study period (2003-2016); in Table 2 the performance scores are evaluated separately for the calibration and validation sub periods. It is worth noting that the model accurately simulates the observed river discharge data and is able to give the "right answer" with good modelling performances. Score values of KGE and R over the calibration (validation) period are higher than 0.62 (0.67) and 0.75 (0.75) (resp.) for all the sections; RRMSE is lower than 46% (51%) for all the sections except for section 9, where it rises up to 71% (77%). The performances remain good even if they are evaluated over the entire study period as indicated by the scores on the top of each plot of Figure 4.

6.2 Cross-validation

The cross-validation has been carried out over the six river sections illustrated in Figure 5 not used in the calibration step. The performance scores on the top of each plot refer to the entire study periods; the scores split for calibration and validation periods are reported in Table 2. For some river sections the performance is quite low (see, e.g., river section 1, 2 and 5) whereas for others the model is able to simulate the observed discharge data quite accurately (e.g., 7 and 8). In particular, for river sections 1 and 2 even if KGE reaches values equal to 0.35 and 0.40 (for the whole period), respectively, there is not a good agreement between observed and simulated river discharge and the R score is lower than 0.55 for both river sections. The worst performance is obtained over section 5, with negative KGE and low R (high RRSME). These results are certainly influenced by the presence of large dams located upstream to these river sections (i.e., Garrison, Gavins Point and Kanopolis dams, see Table 1) which have a strong impact on discharge: the model, not having a specific module for modelling reservoirs, is not able to accurately reproduce the dynamics of river discharge over regulated river sections. Positive KGE values are obtained over river sections 3, 7 and 8. In particular, over section 3 the STREAM v1.3 model overestimates the observed river discharge due the presence of large dams along the Missouri river, over the Great Plains region. This area is well known from other large-scale hydrological models (e. g., ParFlow-CLM and WRF-Hydro) to be an area with very low performances in terms of river discharge modelling (O'Neill et al., 2020, Tijerina et al., 2021).

Over section 7, located over the Rock river, a relatively small tributary of Mississippi river (see Table 1), the STREAM v1.3 model overestimation has to be attributed to: 1) the different characteristics of the Rock river basin with respect to the entire basin closed to section 6 where the model has been calibrated (see Figure 3); 2) the small size of the Rock river basin (23’000 km^2 , if compared with GRACE resolution, 160’000 km^2) for which the model accuracy is expect to be lower. Conversely, the performances over river section 8, whose parameters have been set equal to the ones of river section 10, are quite high (KGE equal to 0.71, 0.80 and 0.77 for the entire, the calibration and the validation period, respectively; R equal to 0.83, 0.84 and 0.84 for the entire, calibration and validation periods, respectively). This outcome demonstrates that under some circumstances, the STREAM v1.3 model can be used to estimate river discharge in basins not calibrated over, especially those without upstream dams and with comparable size and land cover.

Although it is expected that the performances of STREAM v1.3 model, as any hydrological model calibrated against observed data, can decrease over the gauging sections not used for the calibration, the findings obtained above raises doubts about the robustness of model parameters and whether it is actually possible to transfer model parameters from one river section to another with different interbasin characteristics. A more in-depth investigation about the model calibration procedure, with special focus on the regionalization of the model parameters, should be carried out but this topic is beyond the scope of the manuscript.

6.3 External Validation

For the external validation, the monthly runoff time series provided by the GRUN datasets have been compared against the ones computed by the STREAM v1.3 model. For that, STREAM daily runoff time series have been aggregated at monthly scale and re-gridded at the same spatial resolution of the GRUN dataset (0.5°). The comparison is illustrated in Figure 6 for the common period 2003–2014. Although the two datasets consider different precipitation inputs, the two models agree in identifying two distinct zones in terms of runoff, i.e., the western dry and the eastern wet area. This two distinct zones can be clearly identified also in the GSWP3 and TMPA 3B42 V7 precipitation maps (see Figure S1) used as input in GRUN and STREAM v1.3, respectively, stressing that STREAM runoff output is correctly driven by the input data. However, likely due to the calibration procedure, the STREAM runoff map appears patchier with respect to GRUN and discontinuities along the sub-basin boundaries (identified in Figure 3) can be noted. This should be ascribed to the automatic calibration procedure of the model that, differently from other calibration techniques (e. g., regionalization procedures), does not consider the basin physical attributes like soil, vegetation, and geological properties that govern spatial dynamics of hydrological processes. This calibration procedure can generate sharp discontinuities even for neighbouring subcatchments individually calibrated. It leads to discontinuities in model parameter values and consequently in the simulated hydrological variable (runoff).

7. DISCUSSION

In the previous sections, the ability of the STREAM v1.3 model to accurately simulate river discharge and runoff time series has been presented. In particular, Figures 4, 5 and 6 demonstrate that satellite observations of precipitation, soil moisture and terrestrial water storage anomalies can provide accurate daily river discharge estimates for near-natural large basins (absence of upstream dams), and for basins with draining area lower than 160’000 km^2 (see section 7), i.e., at spatial/temporal resolution lower than the ones of the TWSA input data (monthly, 160’000 km^2). This is an important result of the study as it demonstrates, on one hand, that the model structure is appropriate with respect to the data used as input and, on the other hand, the great value of information contained into TWSA data that, even if characterized by limited spatial/temporal resolution, can be used to simulate runoff and river discharge at basin scale. This finding has been also confirmed by a preliminary sensitivity analysis in which the STREAM v1.3 model has been run with different hydrological inputs of precipitation, soil moisture and total water storage anomaly (not shown here for brevity). In particular, by running the STREAM v1.3 model with different input configurations (e.g., by using TMPA 3B42 V7 or Climate Prediction Center (CPC) data for precipitation, ESA CCI or Advanced SCATterometer (ASCAT) data for soil moisture, TWSA or soil moisture data to simulate the slow-flow river discharge component), we found that STREAM results are more sensitive to soil moisture data rather than to precipitation input. In addition, by running STREAM v1.3 model with soil moisture data as input to simulate the slow-flow river discharge component (i.e. without using TWSA data) we found a deterioration of the model results.

Hereinafter, the strengths and the main limitations of the STREAM v1.3 model are discussed.

Among the strengths of the STREAM v1.3 model it is worth highlighting:

1. **Simplicity**. The STREAM v1.3 model structure: 1) limits the input data required (only precipitation, air temperature, soil moisture and TWSA data are needed as input; LSM/GHMs require many additional inputs such as wind speed, shortwave and longwave radiation, pressure and relative

humidity); 2) limits and simplifies the processes to be modelled for runoff/discharge simulation. Processes like evapotranspiration, infiltration or percolation, are not modelled therefore avoiding the need of using sophisticated and highly parameterized equations (e.g., Penman-Monteith for evapotranspiration, Allen et al.,1998, Richard equation for infiltration, Richard, 1931); 3) limits the number of parameters (only 8 parameters have to be calibrated) thus simplifying the calibration procedure and potentially reduce the model uncertainties related to the estimation of parameter values.

2. **Versatility**. The STREAM v1.3 model is a versatile model suitable for daily runoff and discharge estimation over sub-basins with different physiographic characteristics. The results obtained in this study clearly indicate the potential of this approach to be extended at the global scale. Moreover, the model can be easily adapted to ingest input data with spatial/temporal resolution different from the one tested in this study (0.25°/daily). For instance, satellite missions with higher space/time resolution, or near real time satellite products could be considered. As an example, the Next Generation Gravity Mission design studies all encompass double-pair scenarios, which would greatly improve upon the current spatial resolution of single-pair missions like GRACE and GRACE-FO (> 100’000 km^2). The STREAM v1.3 model shows high flexibility also in the possibility to modify the subbasin delineation and to introduce additional observational river discharge data to be used for the model calibration.

3. **Computationally inexpensive.** Due to its simplicity and the limited number of parameters to be calibrated, the computational effort for the STREAM v1.3 model is very limited.”

However, some limitations have to be acknowledged for the current version of the STREAM v1.3 model:

1. **Presence of reservoir, diversion, dams or flood plain**. As the STREAM v1.3 model does not explicitly consider the presence of discontinuity elements along the river network (e. g, reservoir, dam or floodplain), discharge estimates obtained for sections located downstream of such elements might be inaccurate (see, e.g., river sections 1 and 2 in Figure 5).

2. **Need of in situ data for model calibration and robustness of model parameters**. As discussed in the results section, parameter values of the STREAM v1.3 model are set through an automatic calibration procedure aimed at minimizing the differences between simulated and observed river discharge. The main drawback of this parameterization technique is that the models parameterized with this technique may exhibit (1) poor predictability of state variables and fluxes at locations and periods not considered in the calibration, and (2) sharp discontinuities along sub-basin boundaries in state flux, and parameter fields (e.g., Merz and Blöschl, 2004). To overcome these issues, several regionalization procedures, as for instance summarized in Cislaghi et al. (2020), could be conveniently applied to transfer model parameters from hydrologically similar catchments to a catchment of interest. In particular, the regionalization of model parameters could allow to: i) estimate discharge and runoff time series over ungauged basins overcoming the need of discharge data recorded from in–situ networks; ii) estimate the model parameter values through a physically consistent approach, linking them to the characteristics of the basins; iii) solve the problem of discontinuities in the model parameters, avoiding to obtain patchy unrealistic runoff maps. As this aspect requires additional investigations and it is beyond the paper purpose, it will not be tackled here.

By looking at technical reviews of large-scale hydrological models (e.g., Sood and Smakhtin, 2015, Kauffeldt et al., 2016), it can be noted there are many established models, similar in objective and limitations to STREAM v1.3 model, already existing with support and user base (e.g., among others, Community Land Model, CLM, Oleson et al., 2013; European Hydrological Predictions for the Environment, E-HYPE, Lindström et al., 2010; H08, Hanasaki et al., 2008, PCR-GLOBWB, van Beek and Bierkens, 2008; Water – a Global Assessment and Prognosis WaterGAP, Alcamo et al., 2003; ParFlow–CLM, Maxwell et al., 2015; WRF-Hydro, Gochis et al., 2018). Some of them, e.g., ParFlow-CLM or WRF-Hydro have been specifically configured across the continental United States and showed good capability to reproduce observed streamflow data over the Mississippi river basin with performances decreased throughout the Great Plains (O'Neill et al., 2020, Tijerina et al., 2021) which is consistent with the results we obtained with STREAM v1.3 model. However, with respect to classical hydrological and land surface models, STREAM v1.3 is based on a new concept for estimating runoff and river discharge which relies on: (a) the almost exclusive use of satellite observations, and, (b) a simplification of the processes being modelled.

This approach brings several advantages: 1) satellite data implicitly consider the human impact on the water cycle observing some processes, such as irrigation application or groundwater withdrawals, that are affected by large uncertainty in classical hydrological models, 2) the satellite technology grows quickly and hence it is expected that the spatial/temporal resolution and accuracy of satellite products will be improved in the near future (e.g., 1 km resolution from new satellite soil moisture products and the next generation gravity mission); the STREAM v1.3 model is able to fully exploit such improvements; 3) STREAM v1.3 model simulates only the most important processes affecting the generation of runoff, and considers only the most important variables as input (precipitation, surface soil moisture and groundwater storage). In other words, the model does not need to simulate processes, such as evapotranspiration and infiltration and therefore it is an independent modelling approach for simulating runoff and river discharge that can be also exploited for benchmarking and improving classical land surface and hydrological models.

8. CONCLUSIONS

This study presents a new conceptual hydrological model, STREAM v1.3, for runoff and river discharge estimation. By using as input satellite data of precipitation, soil moisture and terrestrial water storage anomalies, the model has been able to provide accurate daily river discharge and runoff estimates at the outlet river section and the inner river sections and over a 0.25°×0.25° spatial grid of the Mississippi river basin. In particular, the model is suitable to reproduce:

1. river discharge time series over the calibrated river section with good performances both in calibration and validation periods;

2. river discharge time series over river sections not used for calibration and not located downstream dams or reservoirs;
3. runoff time series with a quite good agreement with respect to the well-established GRUN observational-based dataset used for comparison.

The integration of observations of soil moisture, precipitation and terrestrial water storage anomalies is a first alternative method for river discharge and runoff estimation with respect to classical methods based on the use of TWSA-only (suitable for river basins larger than 160’000 km², monthly time scale) or on classical LSMs (Cai et al., 2014).

Moreover, although simple, the model has demonstrated a great potential to be easily applied over subbasins with different climatic and topographic characteristics, suggesting also the possibility to extend its application to other basins. In particular, the analysis over basins with high human impact, where the knowledge of the hydrological cycle and the river discharge monitoring is very important, deserves special attention. Indeed, as the STREAM v1.3 model is directly ingesting observations of soil moisture and terrestrial water storage data, it allows the modeller to neglect processes that are implicitly accounted for in the input data. Therefore, human-driven processes (e.g., irrigation, land use change), that are typically very difficult to simulate due to missing information and might have a large impact on the hydrological cycle, hence on total runoff, could be implicitly modelled. The application of the STREAM v1.3 model on a larger number of basins with different climatic-physiographic characteristics (e.g., including more arid basins, snow-dominated, lots of topography, heavily managed) will allow to investigate the possibility to regionalize the model parameters and overcome the limitations of the automatic calibration procedure highlighted in the discussion section.

AUTHOR CONTRIBUTION

S.C. performed the analysis and wrote the manuscript. G.G. collected the data and helped in performing the analysis; C.M, L.B., A.T., N.S., H.H.F., C.M., M.R. and J.B. contributed to the supervision of the work. All authors discussed the results and contributed to the final manuscript.

CODE AVAILABILITY

The STREAM model version 1.3, with a short user manual, is freely downloadable in Zenodo (https://zenodo.org/record/4744984, doi: 10.5281/zenodo.4744984). The STREAM v1.3 model code is distributed through M language files, but it could be run with different interpreters of M language, like the GNU Octave (freely downloadable here https://www.gnu.org/software/octave/download).

DATA AVAILABILITY

All data and codes used in the study are freely available online. Air temperature data are available at https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html (last access 25/11/202). In situ river discharge data have been taken from the Global Runoff Data Center (GRDC, https://www.bafg.de/GRDC/EN/Home/homepage_node.html (last access 25/11/202). Precipitation and soil moisture data are available from http://pmm.nasa.gov/data-access/downloads/trmm and https://esa-soilmoisture-cci.org/, respectively.

COMPETING INTERESTS

The authors declare that they have no conflict of interest.

ACKNOWLEDGMENTS

The authors wish to thank the Global Runoff Data Centre (GRDC) for providing most of the streamflow data throughout Europe. The authors gratefully acknowledge support from ESA through the STREAM Project (EO Science for Society element Permanent Open Call contract n° 4000126745/19/I-NB).

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Table 1. Location of gauging stations over the Mississippi basins and upstream contributing area. Bold text is used to indicate stations where the STREAM v1.3 model has been calibrated.

#	**River**	**Station name**	**Latitude (°)**	**Longitude (°)**	**Upstream area (km^2)**	**Mean annual river discharge (m^3/s)**	**Presence of dam**
1	Missouri	Bismarck, ND	-100.82	46.81	481’232	633	Garrison dam
2	Missouri	Omaha, NE	-95.92	41.26	814’371	914	Gavins Point Dam
3	Missouri	Kansas City, MO	-94.59	39.11	1’229’427	1499	---
4	**Missouri**	**Hermann, MO**	**-91.44**	**38.71**	**1’330’000**	**2326**	**---**
5	Kansas	Wamego, KS	-96.30	39.20	143’054	141	Kanopolis
6	**Mississippi**	**Keokuk, IA**	**-91.37**	**40.39**	**282’559**	**1948**	**---**
7	Rock	Near Joslin, IL	-90.18	41.56	23’835	199	---
8	Mississippi	Chester, IL	-89.84	37.90	1’776’221	6018	---
9	**Arkansas**	**Murray Dam Near Little Rock, AR**	**-92.36**	**34.79**	**408’068**	**1249**	**---**
10	**Mississippi**	**Vicksburg, MS**	**-90.91**	**32.32**	**2’866’590**	**17487**	**---**
11	**Ohio**	**Metropolis, ILL.**	**-88.74**	**37.15**	**496’134**	**7931**	**---**

Table 2. Performance scores obtained over the Mississippi river sections during the calibration and validation periods.

#	**CALIBRATION PERIOD**			**VALIDATION PERIOD**		
SCORE	KGE (-)	R (-)	RRMSE (%)	KGE (-)	R (-)	RRMSE (%)
CALIBRATED SECTIONS						
10	0.78	0.78	30	0.74	0.80	38
9	0.62	0.75	71	0.67	0.85	77
6	0.83	0.84	39	0.73	0.84	46
4	0.77	0.78	46	0.72	0.75	50
11	0.82	0.82	44	0.70	0.86	51
SECTIONS NOT USED FOR CALIBRATION						
1	-3.26	0.08	137	0.20	0.44	96
2	-0.57	0.48	118	0.40	0.53	89
3	0.16	0.71	83	0.39	0.70	72
5	-1.49	0.24	368	-1.26	0.31	358
7	0.53	0.68	71	0.20	0.70	81
8	0.80	0.84	36	0.77	0.84	39

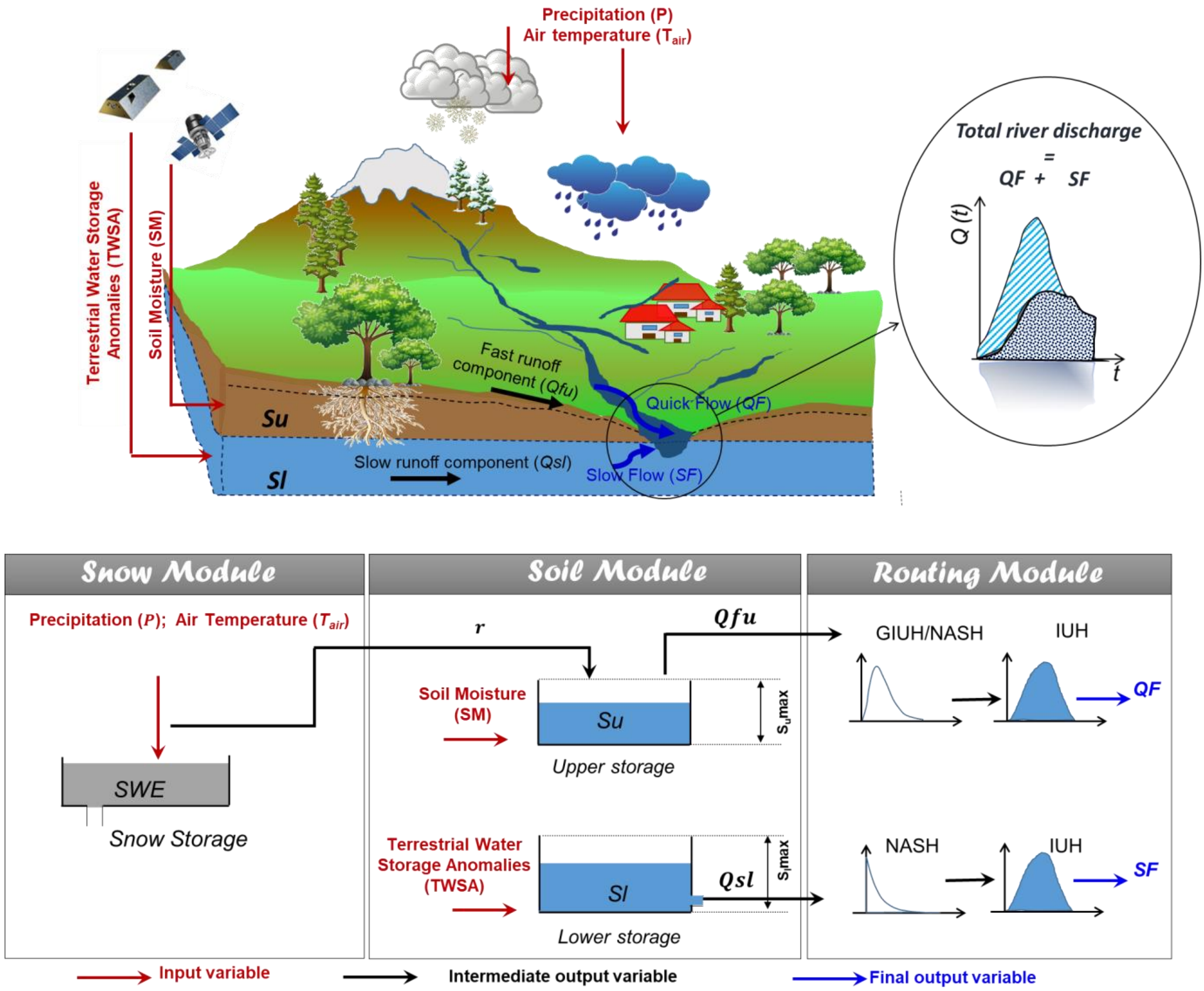

Figure 1. Configuration of the STREAM v1.3 model adopted for total runoff estimation. The model includes three modules, the snow module allowing to separate snowfall from precipitation, the soil module that simulates the slow and quick runoff components (*Qsu* and Qfu, respectively) and the routing module for flood simulation. Red arrows indicate input variables; black arrows indicate intermediate output variables; blue arrows indicate final output variables. The components *Qfu* and *Qsu* are computed by using satellite *P*, soil moisture and TWSA data as input to the soil module. Please refer to text for symbols.

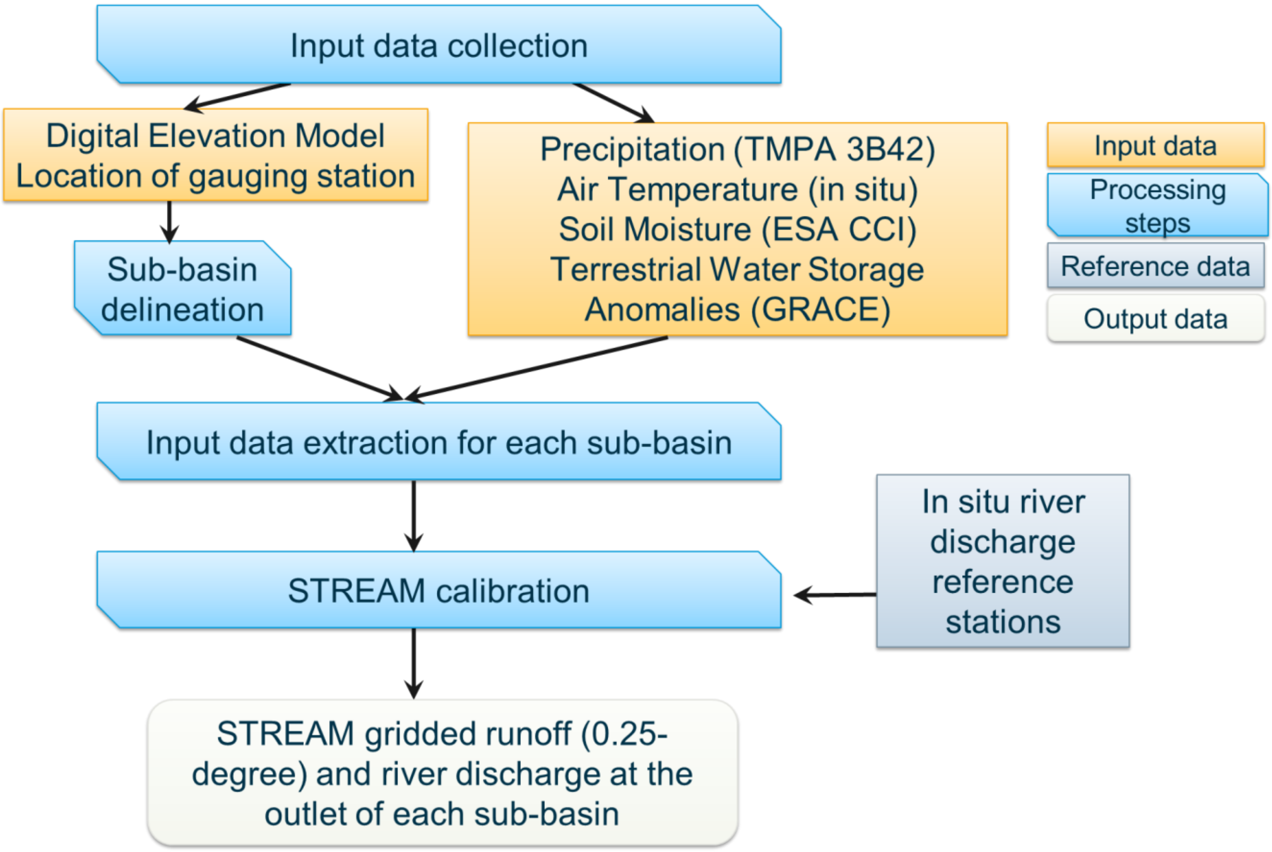

Figure 2. Processing steps of the STREAM v1.3 model.

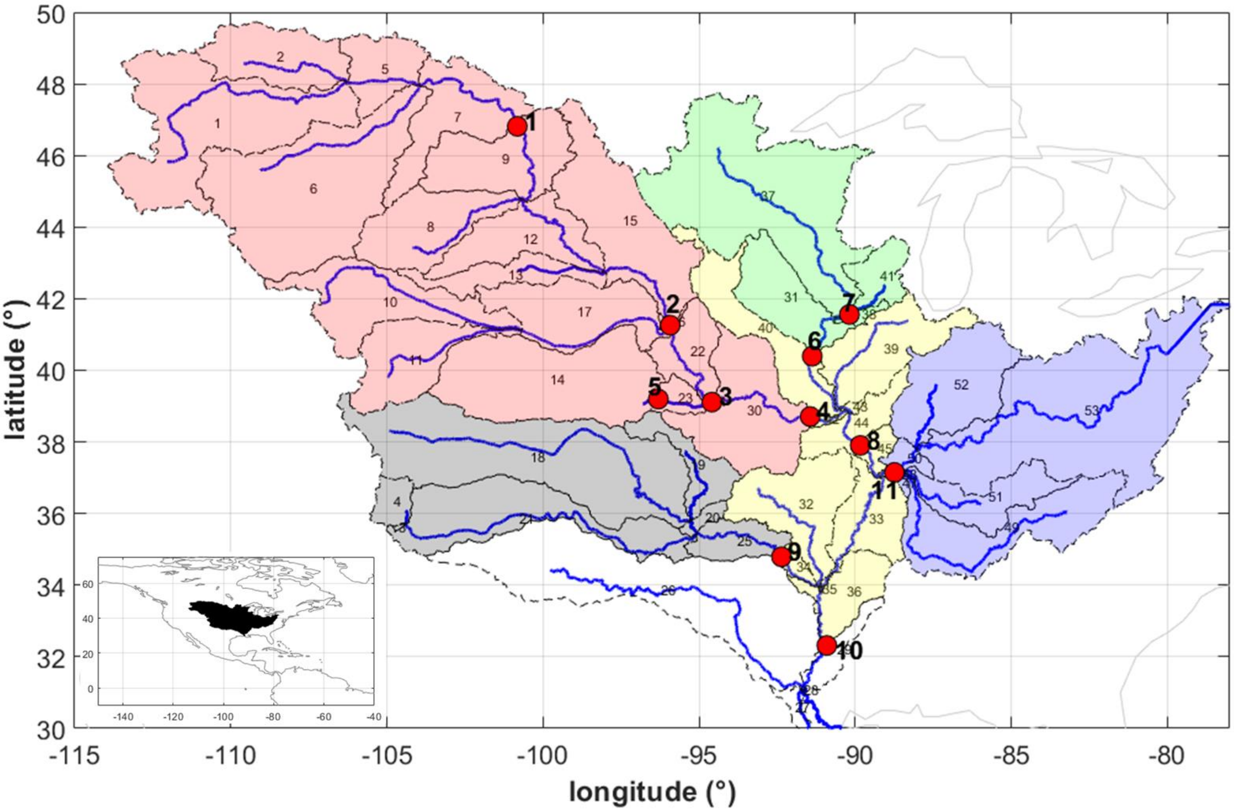

Figure 3. Mississippi sub-basin delineation. Red dots indicate the location of the discharge gauging stations; different colours identify different inner sections (and the related contributing sub-basins) used for the model calibration.

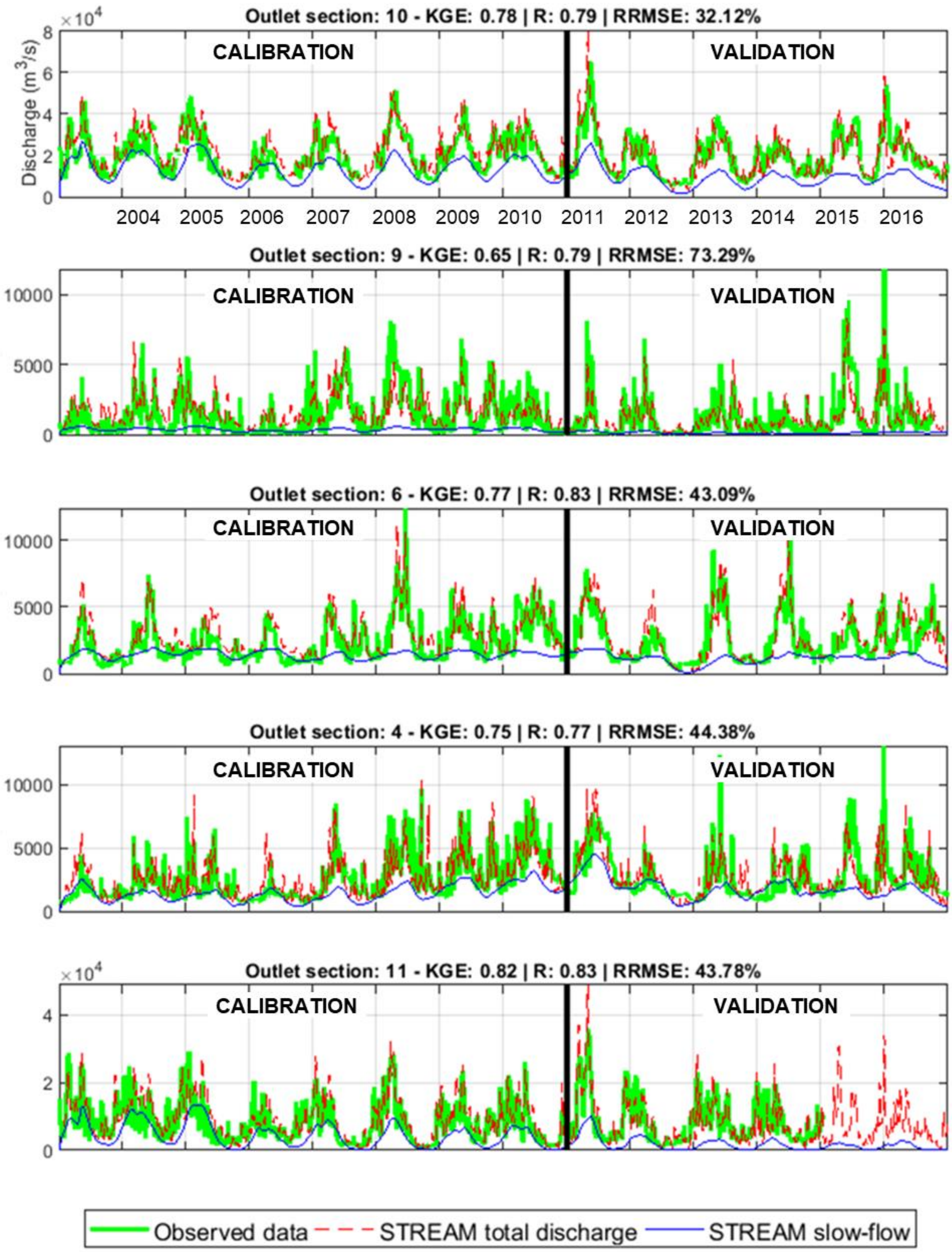

Figure 4. Comparison between observed and simulated river discharge time series over the five calibrated sections over Mississippi river basin. Performance scores at the top of each plot refer to the entire study period (2003–2016).

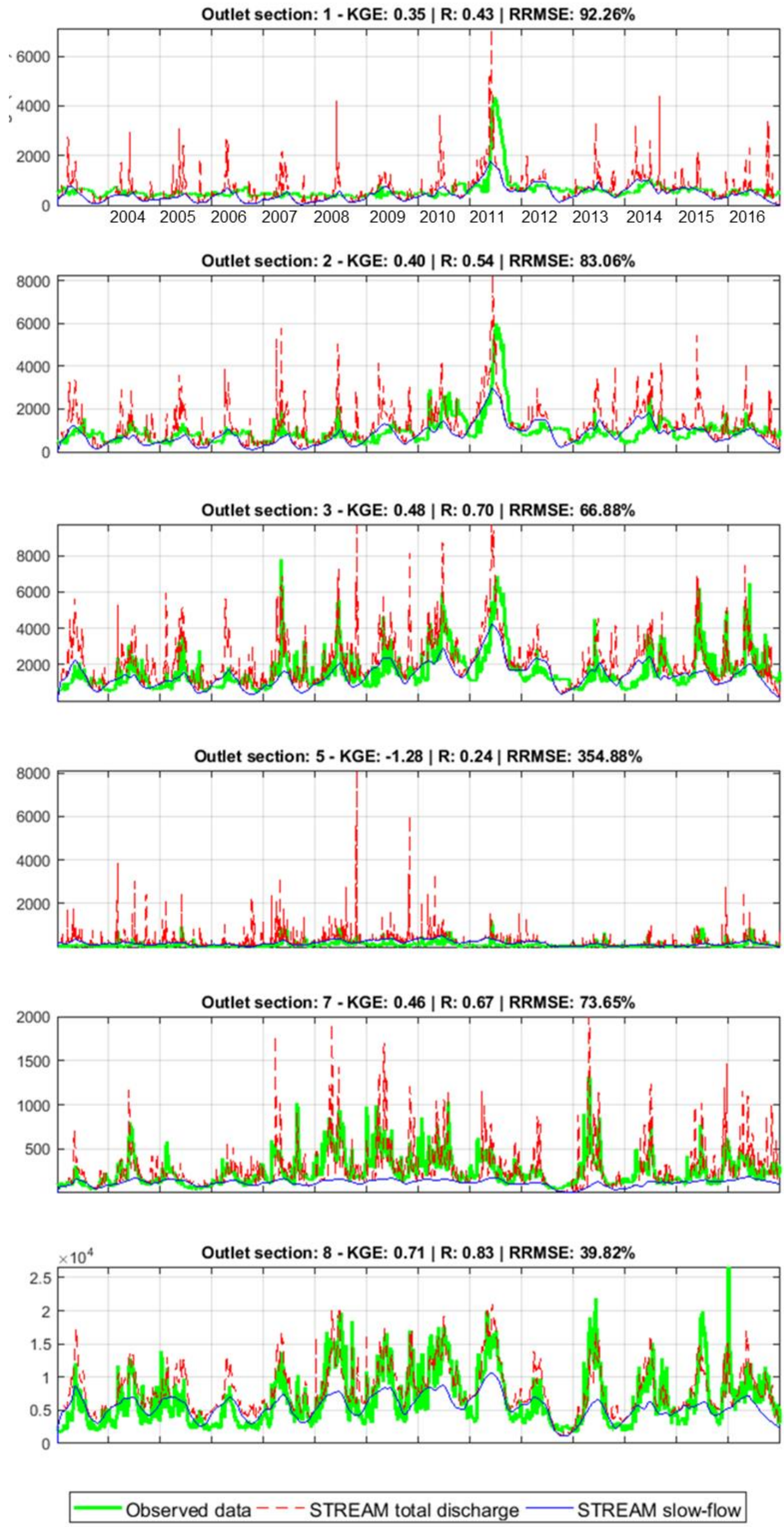
Outlet section: 1 - KGE: 0.35 | R: 0.43 | RRMSE: 92.26%
Outlet section: 2 - KGE: 0.40 | R: 0.54 | RRMSE: 83.06%
Outlet section: 3 - KGE: 0.48 | R: 0.70 | RRMSE: 66.88%
Outlet section: 5 - KGE: -1.28 | R: 0.24 | RRMSE: 354.88%
Outlet section: 7 - KGE: 0.46 | R: 0.67 | RRMSE: 73.65%
Outlet section: 8 - KGE: 0.71 | R: 0.83 | RRMSE: 39.82%
Observed data
STREAM total discharge
STREAM slow-flow

Figure 5. Comparison between observed and simulated river discharge time series over the gauged sections not used in the calibration phase. Performance scores at the top of each plot refer to the entire study period (2003–2016).

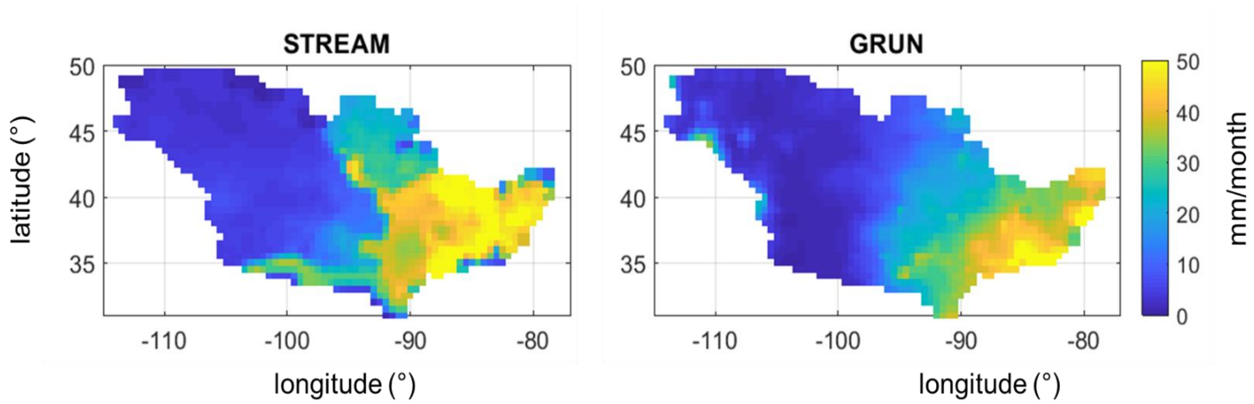

Figure 6. Mississippi river basin: mean monthly runoff for the period 2003–2014 obtained by STREAM v1.3 and GRUN models.

APPENDIX

Table 1A. Description of STREAM v1.3 parameters, belonging module, variability range and unit.

Parameter	Description	Module	Range Variability	Unit
Cm	degree-day coefficient	Snow	0.1/24-3	[-]
α	exponent of infiltration	Soil	1-30	[-]
T	characteristic time length	Soil	0.01-80	[days]
β	coefficient relationship slow runoff component and TWSA	Soil	0.1-20	[mm h-1]
m	exponent in the relationship between slow runoff component and TWSA	Soil	1-15	[-]
$\boldsymbol{\gamma}$	parameter of GIUH	Routing	0.5-5.5	[-]
C	Celerity	Routing	1-60	[km h-1]
D	Diffusivity	Routing	1-30	[km2 h-1]

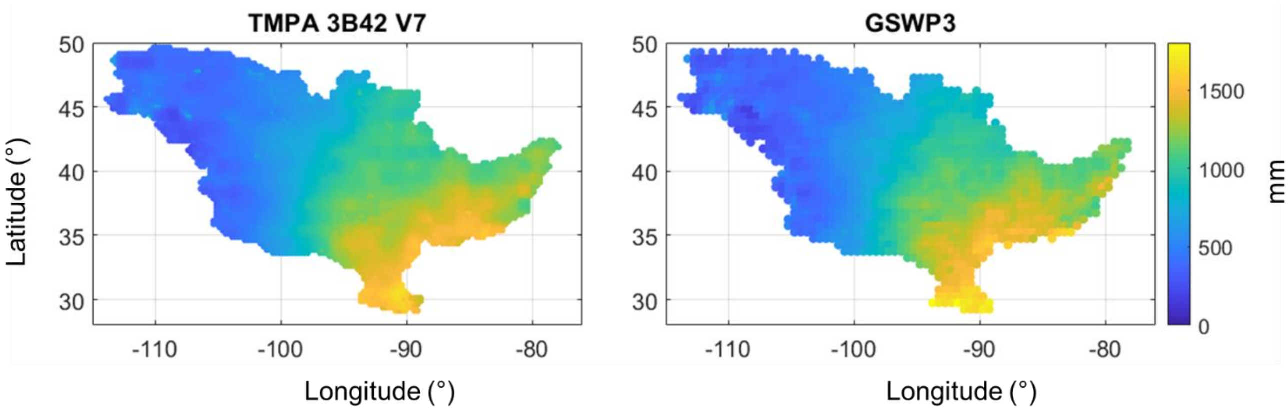

Figure S1. Mean annual precipitation data over the period 2003-2014 obtained by TMPA 3B42 V7 and GSWP3 datasets over the Mississippi river basin.