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Review

The Role of Satellite-Based Remote Sensing in Improving Simulated Streamflow: A Review

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Abstract: A hydrological model is a useful tool to study the effects of human activities and climate change on hydrology. Accordingly, the performance of hydrological modeling is vitally significant for hydrologic predictions. In watersheds with intense human activities, there are difficulties and uncertainties in model calibration and simulation. Alternative approaches, such as machine learning techniques and coupled models, can be used for streamflow predictions. However, these models also suffer from their respective limitations, especially when data are unavailable. Satellite-based remote sensing may provide a valuable contribution for hydrological predictions due to its wide coverage and increasing tempo-spatial resolutions. In this review, we provide an overview of the role of satellite-based remote sensing in streamflow simulation. First, difficulties in hydrological modeling over highly regulated basins are further discussed. Next, the performance of satellite-based remote sensing (e.g., remotely sensed data for precipitation, evapotranspiration, soil moisture, snow properties, terrestrial water storage change, land surface temperature, river width, etc.) in improving simulated streamflow is summarized. Then, the application of data assimilation for merging satellite-based remote sensing with a hydrological model is explored. Finally, a framework, using remotely sensed observations to improve streamflow predictions in highly regulated basins, is proposed for future studies. This review can be helpful to understand the effect of applying satellite-based remote sensing on hydrological modeling.

Keywords: satellite-based remote sensing; streamflow simulation; hydrological model; data assimilation

1. Introduction

Rivers, as the primary links between the land and ocean, play an important role in global water and energy cycles [1]. In past decades, hydrological processes and their related biogeochemical cycles in rivers have been dramatically modified as a consequence of climate and anthropogenic changes [1–9]. Especially in coastal regions with high population density and severe water shortages, intense human activities (such as land use change, urban expansion, cascade dam construction, farmland fertilization, large-scale livestock and poultry breeding, and industrial sewage discharge) pose increasing stresses to coastal ecosystems. Consequently, problems associated with the ecology and environment are very serious in these areas, particularly in the continuum of watershed, estuary, and offshore areas, such as hydrological rhythm anomalies, river channel runoff-cutting, the decrease of freshwater flux into the sea, wetland shrinkages in estuaries, seawater intrusion, offshore seawater pollution, and the decline or disappearance of land–sea ecological connectivity [7,10–14]. In such regions, hydrological processes present high nonlinearity and complexity, which cause huge challenges for accurately describing hydrological behavior. However, understanding and simulating hydrological processes is crucial for reasonable water resource utilization and management in these regions.

A hydrological model is a useful tool for hydrological predictions [15–17]. Particularly distributed hydrological models, which are able to reproduce the spatial and temporal evolution of a variety of hydrological processes, have been widely used for detecting changes in the hydrological regime due to human activity or/and climate change, real-time flood forecasting, drought monitoring, and water resource management [5,18–22]. Accordingly, the performance of hydrological modeling is critically important for the accurate representation of hydrological cycles [23]. However, a number of factors, such as limited ground observations and their poor temporal and spatial representativeness, inaccurate model input forcing, imperfect model structures, and empirical model parameters, may result in a degree of uncertainty in model simulations [16,24–30]. Especially in watersheds mainly governed by human decisions, there are considerable difficulties and great uncertainties in model calibration and prediction, possibly leading to incorrect model parameterization and model estimates [25,31,32].

For this reason, data-driven models, such as machine learning (ML) techniques for empirical rainfall-runoff modeling, have been proposed as a useful complement to hydrological models in the past decade [33]. For example, Artificial neural networks (ANNs), regression trees, and support vector machines (SVM) have been shown to powerful tools for discharge predictions, particularly in catchments with complex and non-linear hydrological behaviors or limited data [33–36]. The integration of a hydrological model with recurrent neural networks can also improve the accuracy of streamflow forecasting [36]. However, these data-driven models exhibit respective limitations. For instance, although the popular ANNs models do not require information on the complex nature of hydrological processes, they suffer from overfitting or overtraining, which may result in large errors in out-of-sample predictions [33,37,38]. It is essential to compare different approaches and choose appropriate ML approaches for hydrological predictions.

Another issue of hydrological modeling is that traditional streamflow calibration may produce low simulation accuracy for other hydrological variables, such as soil moisture, groundwater, and evapotranspiration [25,28,39–41]. Consequently, additional variables (e.g., soil moisture, evapotranspiration, and snow water equivalents), along with streamflow observations, have been applied for better model performance. Model calibration [40,42–44] and data assimilation [32,45–49], as well as their integration [50], can be used to incorporate multivariable into hydrological models to improve hydrological modeling. Especially, data assimilation shows great potential because it can update hydrological states and model parameters concurrently [45,46,49].

Moreover, some coupled models, which do not always require calibration, have been developed during the past decade (e.g., the Hydrological Modeling and Analysis Platform (HyMap) [51] and the Weather Research and Forecasting Model Hydrological modeling extension package (WRF-Hydro) [52]. These models couple atmospheric models, land surface models, and hydrologic models to produce good discharge simulations [51,52]. However, they are more appropriate for large-scale catchments. More importantly, the lack of sufficient datasets would restrict the utility of these models.

Overall, the aforementioned approaches can help greatly to enhance hydrological predictions, but their applications suffer from different limitations, especially when data are unavailable. Fortunately, satellite-based remote sensing can provide an alternative to observations of different hydrological variables (e.g., remotely sensed precipitation, evapotranspiration, soil moisture, snow water equivalents, etc.) for hydrological modeling, which have been reported by a large number of studies (e.g., [20,31,39,40,49,53]). Winsemius (2009) [54] gave a brief overview of the remote sensing estimates of hydrologic variables and their further applications in hydrological modeling. However, the satellite information was out of date and was limited only to the terrestrial water storage (TWS) from the Gravity Recovery and Climate Experiment (GRACE), satellite-based evaporation, and rainfall estimates. Sheffield et al. (2018) [55] provided an overview about the current and potential future role of satellite remote sensing in improving water resource management. However, their review has focused on examples for Latin America Caribbean (LAC), and has emphasized water resource management rather than hydrological modeling.

In view of this, we comprehensively summarize the role of satellite-based remote sensing in streamflow simulations. In Section 2, difficulties in hydrological modeling over highly regulated basins are further discussed. Section 3 provides an overview of the performance of satellite-based remote sensing in enhancing simulated streamflow. Section 4 introduces the application of data assimilation for merging satellite-based remote sensing with a hydrological model. Section 5 offers summaries and discussions, as well as outlooks. Particularly, future studies are recommended to determine how to apply remotely sensed observations for improving simulated streamflow in highly regulated basins.

2. Difficulties in Hydrological Modeling over Highly Regulated Basins

A distributed hydrological model, as a physically-based model, requires numerous ground observations as well as model parameter optimization. The scarcity or spatial mismatch of observed data will restrict the model application [28]. Moreover, human activity, particularly water consumption and cascade dam construction, further increases the difficulty in hydrological forecasting. To perform hydrological modeling in human-impacted watersheds, Wang and Jia (2016) [7] established a nature–society dualistic water cycle theory to support effective solutions for water-related issues. This theory has greatly promoted the research progress of water cycle evolution mechanisms. Based on this theory, Sang et al. (2008) [56] developed an agriculture management module and a consumptive water use module, which updated the Soil and Water Assessment Tool (SWAT) model. Their results showed that the updated model could be applied successfully to the highly regulated region (Tianjin City of China). Zhang et al. (2011) [57] developed a water quantity and quality joint mode of dam and floodgate operations based on the SWAT model, which more realistically simulated the process of water quantity and quality controlled by dams and floodgates in the Wenyu River basin of Beijing city.

The aforementioned improvement in hydrological models can help to simulate water quantity and quality in watersheds under strong human influence. Nevertheless, this work is still hampered by data scarcity or mismatches. On the one hand, the survey data for water consumption or its estimation commonly have coarser spatial and temporal resolutions, which cannot elaborate inter-annual and intra-annual variations in water consumption. Furthermore, there is difficulty in extending these data to the spatial dimension of distributed hydrological models, because the primary spatial unit of these models is the grid or sub-basin (and further hydrologic response unit). On the other hand, it is difficult to gain observed inflow and outflow data for reservoirs and dams. Moreover, there is significant randomness for the artificial regulation of reservoirs and dams. Additionally, there may be no monitoring stations for many small and medium-sized reservoirs and dams. These disadvantages can significantly affect the performance of hydrological modeling.

In addition, hydrological model calibration using streamflow observations alone would be questionable. Commonly, hydrological models have been calibrated by adjusting model parameters to make the simulated streamflow agreeing with observations (particularly at the outlet of a watershed) [58,59], but a calibrated parameter set with the satisfactory results of a simulated streamflow at a limited number of discharge locations does not warrant the performance at most locations within a watershed [25,28,60]. Moreover, streamflow-only calibration, except for the inaccurately observed meteorological forcing inputs (e.g., precipitation and temperature) and the imperfect model structure, may also reproduce unreliable simulation results of a second model output variable, as mentioned above [39,40,61].

In general, the aforementioned deficiencies can lead to large uncertainties in hydrological modeling, which would hinder the application of hydrological models.

3. The Role of Satellite-Based Remote Sensing in Improving Simulated Streamflow

3.1. Remotely Sensed Precipitation

Precipitation is a major component of the hydrologic cycle and is the critical input for hydrological models [62–74]. Accurate and continuous precipitation estimates are essential for reliable hydrological simulations of fluxes and states [17,73,75]. However, poor precipitation observations (e.g., poor continuity in time and space) may lead to non-linear propagated errors in streamflow simulations [66,76–79]. This, possibly, results in unsatisfactory model performance. In addition, the precision of precipitation data may significantly affect the capability of other remotely sensed data (regarding evapotranspiration, soil moisture, snow properties, terrestrial water storages changes (TWSC), etc.) for improving streamflow estimates. Hence, appropriate precipitation data are the prerequisite for guaranteeing hydrological modeling.

Traditional rain gauge measurements can provide accurate precipitation data, but uneven spatial coverage or scarce rain gauges may cause great uncertainty [64,66,78,80–82]. In contrast, a variety of satellite precipitation products, such as Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) [83], Integrated Multi-satellite Retrievals for Global Precipitation Measurement (GPM-IMERG), which is a global successor to TRMM [84], Climate Prediction Center Morphing technique (CMORPH) [85], Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) [86], Global Satellite Mapping of Precipitation (GSMaP) [87], and Naval Research Laboratory Global Blended-Statistical Precipitation Analysis Data (NRL-Blend) [88], can offer a promising alternative source on a global scale, with increasing temporal and spatial resolutions. These products have been applied in a wide range of hydrological applications from water resource modeling to drought and flood monitoring (e.g., [68–70,73,74,76,79,89–96]) (Table 1).

In general, the capability and feasibility of satellite rainfall estimate (SRE) in driving hydrological models vary largely due to differences in topography, season, climate, basin size, selected hydrological model, and satellite product type [17,63,69,73,79,91,97–100]. SREs demonstrate a potential hydrologic ability in data-sparse, ungauged, or large-scale catchments, compared to in situ rainfall measurements (e.g., [65,72,76,91–93,97,100]). For instance, Yuan et al. (2018) [72] assessed the hydrologic utility of IMERG and TMPA 3B42 Version 7 in the Yellow Source Region with a sparse rain-gauge network. Their results indicated that, generally, both the IMERG- and 3B42V7-forced daily streamflow simulations were slightly less accurate than those driven by the gauge-based precipitation input in the calibration period, but the performance of the IMERG-based simulation in the validation period surpassed even the model run using the gauge-based precipitation data set. However, in most other areas, SREs have the difficulty to outperform or be equal to rain gauges for rainfall estimates and further hydrological applications due to their seasonal and regional systematic biases and random errors [63,74,89,91,94,100–102].

Therefore, prior to their implementation to the hydrological model, SREs require thorough validation and commonly need bias correction based on rain gauge data [17,71,74,78,89,91,102,103]. Falck et al. (2018) [75] concluded that the corrected radar rainfall estimates reduced the systematic error of the streamflow ensemble for most sub-basins compared with the rain gauge, and significantly improved the simulated streamflow during nine flood events. Zhang et al. (2019) [17] discovered that the adjusted TMPA 3b42V7 improved the performance of the simulated streamflow better than the original TMPA 3b42V7 data, and performed even better than rain-gauge observation in the validation period.

In addition, some studies showed that the model recalibration employing SREs could increase the performance of the streamflow simulation, comparable to the model calibrated with rain gauge data [63,72,89,91,96,104], because the new parameter settings can compensate for errors in the satellite rainfall forcing [79]. For example, Yuan et al. (2018) [72] found that the input-specific model recalibration effectively improved the performance of the daily streamflow simulations using IMERG (Nash Sutcliffe Efficiency (NSE) was 0.856) and 3B42V7 (NSE = 0.840), exceeding that of the gauge-forced model run (NSE = 0.807). However, it should be noted that the parameter values through recalibrating models with SREs may be unrealistic, thereby limiting the model's predictive capability at the sub-basin scale [79].

Overall, a number of studies evaluated the hydrologic utility of different SREs, but most studies have demonstrated the limited capability of SREs as the input forcing, compared to ground observations. Thus, in the future, remote sensing rainfall products have still a long way from replacing ground observations, which produce the most accurate hydrological simulations [102].

Table 1. Relevant studies using satellite-based precipitation products to drive hydrological simulations.

Study	Data (Resolution)	Hydrological Model	Catchment (Area)	Major Findings
Yilmaz et al. (2005) [63]	PERSIANN (0.5 h, 0.25°)	SAC-SMA model	Seven basins of varying sizes and geographic locations within the southeastern United States (from 1346 km^2 to 4774 km^2)	The bias in precipitation estimates and basin size affected the overall performance of the simulated flows when using SRE as the input forcing, with poorer performance in smaller basins and better performance in larger basins. The recalibration of model parameters when SRE was used as the model input obviously improved the model performance.
Su et al. (2008) [97]	TMPA 3B42V6 (3 h, 0.25°)	VIC model	La Plata basin (320,000 km^2)	The TMPA-driven simulations could capture the daily flooding events and represent low flows, but peak flows tended to be biased upward.
Yong et al. (2010) [90]	TMPA 3B42V6 and 3B42 Real Time (RT) (3 h, 0.25°)	VIC-3L model	Laohahe basin (18,112 km^2)	The VIC-3L model was unable to tolerate the nonphysical overestimation behavior of 3B42RT through hydrologic integration processes, while 3B42V6 provided much better hydrologic predictions with a reduced error propagation from input to streamflow at daily and monthly scales.
Stisen and Sandholt (2010) [89]	CMORPH (daily, 8 km), TAMSAT CCD and CPC-FEWS V2 (daily, 11 km), TRMM 3B42V6 and PERSIANN (daily, 27 km)	MIKE SHE model	Senegal River basin in west Africa (350,000 km^2)	The model performance (WBL and RMSE) of simulated discharge was generally poorer using SREs compared with rain gauge data, but some SREs, such as CPC-FEWS and CCD data, performed equally well or better for the parameter NSE than rain gauge data for the subcatchments Qualia and Gourbassa.
Bitew et al. (2011) [91]	CMORPH, TMPA 3B42V6, 3B42RT, and PERSIANN (3 h, 0.25°)	MIKE SHE model	Gilgel Abay watershed with high elevation (1656 km^2)	CMORPH and TMPA 3B42RT exhibited more consistent performance in streamflow simulations, but PERSIANN displayed lower performance, and TMPA 3B42V6 showed the lowest performance in the streamflow simulation.
Xue et al. (2013) [92]	TMPA 3B42V6 and 3B42V7 (3 h, 0.25°)	CREST model	Wangchu Basin (3350 km^2)	The 3B42V6-based simulation exhibited a limited hydrologic prediction skill at daily and monthly scales, while 3B42V7 performed fairly well at both time scales, with a comparable skill score with the gauge rainfall simulations.
Meng et al. (2014) [93]	TMPA 3B42V6 (3 h, 0.25°)	CREST model	Source region of the Yellow River (122,000 km^2)	TMPA cannot be used to drive hydrological models for daily streamflow simulation.
Skinner et al. (2015) [76]	TAMSAT (15 min, 0.5°)	Pitman model	Bakoye catchment (86,000 km^2) with very sparse rain-gauges	The TAMSAT ensemble SRE reduced a mean RMSE to 61.7% of the mean wet season discharge, but poor representations of trace and zero rainfall by SREs were propagated through a hydrological model.
Ashouri et al. (2016) [94]	PERSIANN-CDR (daily, 0.25°), TMPA 3B42V7 (3 h, 0.25°)	HLRDHM model	SAVOY, ELMSP, and SLOA4 basins (337 km^2, 433 km^2, 1489 km^2, respectively)	PERSIANN-CDR and TMPA-derived streamflow simulations were comparable to USGS observations. The capability of PERSIANN-CDR was proven for long-term hydrological rainfall-runoff modeling and streamflow simulation.
Tuo et al. (2016) [105]	CHIRPS (daily, 0.05°), TRMM 3B42V7 (3 h, 0.25°)	SWAT model	Adige River basin (12,100 km^2)	SWAT models with the CHIRPS dataset provided satisfactory streamflow estimation, which makes them a favorable choice for the Alpine region facing data scarcity. However, the TRMM dataset for streamflow modeling generally resulted in unsatisfactory results.
Tang et al. (2016) [67]	TMPA 3B42V7 and 3B42RT (3 h, 0.25°), IMERG V03 (0.5 h, 0.1°)	CREST model	Ganjiang River basin (81,258 km^2)	The IMERG product performed comparably to gauge reference data in daily hydrological simulation. In contrast, TMPA 3B42V7 showed acceptable hydrological performance but less reliable skill for TMPA 3B42RT.
Sun et al. (2016) [77]	TRMM 3B42V7 and CMORPH CRT (3 h, 0.25°), CMORPH BLD and CMORPH CMA (daily, 0.25°)	VIC model	The upper region of Bengbu station over Huaihe River basin (121,300 km^2)	The general streamflow pattern was well captured at daily and monthly scales by the simulations using four satellite–gauge precipitation estimates as the input forcing. CMORPH CRT demonstrated the worst simulations in both long-term streamflow and extreme flood events, while CMORPH CMA forced streamflow simulations even outperformed gauge observations and also displayed superiority in flood monitoring.

Table 1. *Cont.*

Study	Data (Resolution)	Hydrological Model	Catchment (Area)	Major Findings
Gao et al. (2017) [100]	TMPA 3B42V7 and 3B42RT (3 h, 0.25°)	CREST model	Jialing River basin (156,736 km^2) and Tuojiang River basin (196,613 km^2)	When SRE was used to drive the CREST model, the larger basin was more likely to produce satisfactory results for streamflow simulation and flood frequency analysis than the smaller basin under similar circumstances. The 3B42V7 showed higher hydrologic utility than 3B42RT, but their model performance was worse than gauge-based precipitation.
Zubieta et al. (2017) [95]	IMERG V03 (0.5 h, 0.1°), TMPA 3B42V7 and 3B42RT (3 h, 0.25°)	MGB-IPH model	Amazon Basin of Peru and Ecuador (878,300 km^2)	Similar to TMPA 3B42V7 or 3B42V7RT datasets, IMERG was useful for estimating observed streamflows in southern regions, but three SREs did not properly simulate streamflows in northern regions.
Wang et al. (2017) [96]	IMERG-E, IMERG-L, and IMERG-F (V03, 0.5 h, 0.1°), TRMM 3B42V7 (3 h, 0.25°)	VIC model	Beijiang River Basin (38,672 km^2)	The IMERG-F had better hydrological utility than TMPA 3B42V7. The IMERG-E and IMERG-L had satisfactory hydrological utility during the flood season but performed poorly in the whole simulation period. The hydrological performances were significantly improved through model recalibration using each SRE product, but were still worse than those using ground observations.
Zhu et al. (2018) [69]	Fengyun (daily, 0.1°), TMPA 3B42V7, and 3B42RT (daily, 0.25°), CMORPH BLD and CMORPH RAW (daily, 0.25°)	SWAT model	Huifa River basin in the northeast of China (12,385 km^2)	Satisfactory model performances (NSE > 0.5) were achieved at daily scales for Fengyun, TRMM 3B42, and gauge-driven models, and very good performances (NSE > 0.75) at a monthly scale for Fengyun and the gauge driven model. However, CMORPH_BLD, CMORPH_RAW, and TRMM 3B42RT exhibited bad NSE and R^2 at a daily scale.
Li et al. (2018) [68]	TMPA 3B42V7, 3B42RT (3 h, 0.25°)	SWAT model	Tiaoxi watershed (5900 km^2)	TRMM 3B42V7 could properly describe the runoff volume and its composition, but this product was not suitable for daily streamflow simulation purposes.
Falck et al. (2018) [75]	SIMEPAR S-band Doppler radar (5 min, 1 km)	MHD-INPE model	A cascade of sub-basins of Iguaçu catchment (from 1808 km^2 to 21,536 km^2)	The radar rainfall estimates corrected by the SREM2D error model reduced the systematic error of the streamflow ensemble for most sub-basins, compared with the rain gauge. The use of SREM2D significantly improved the simulated streamflow and reduced the overestimation in the cumulative streamflow volumes during nine flood events.
Qi et al. (2018) [70]	TMPA 3B42V7 and 3B42RT, GLDAS-1 (3 h, 0.25°), GSMaP-MVK+ V6 (1 h, 0.1°), PERSIANN (3 h, 0.25°), APHRODITE V1101R1 (daily, 0.25°)	WEBDHM and TOPMODEL model	Biliu basin (2814 km^2)	Increased NSE up to 0.97 and 0.85 in training and validation periods respectively by developing an ensemble-based dynamic Bayesian averaging approach (e-Bay), which used six global fine-resolution precipitation products and two hydrological models of different complexities.
Worqlul et al. (2018) [71]	MPEG (15 min, 3 km)	HBV model	Gilgel Abay and Gumara watersheds (1650 km^2 and 1284 km^2 respectively)	The original SRE resulted in poorer performance for simulated flow than the gauge rainfall, but the model derived by the bias-corrected SRE performed well in capturing the observed flow.
Camici et al. (2018) [106]	TMPA 3B42RT (V7), CMORPH, and PERSIANN (3 h, 0.25°), SM2RAIN$_{CCI}$ (daily, 0.25°)	MISDc model	15 basins in the Mediterranean area (109–4820 km^2)	Compared with ground observations, SRE performed poorly to the drive MISDc model, with the worst results in smaller basins (<500 km^2). However, the integrated SREs provided relatively better performance and even outperformed ground observed data for some basins.
Yuan et al. (2018) [72]	TMPA 3B42V7 (3 h, 0.25°), IMERG V05 (0.5 h, 0.1°)	The grid-based Xinanjiang (GXAJ) model	Yellow River source region (122,000 km^2)	The 3B42V7 and IMERG-driven model run presented acceptable hydrological simulation skill at daily time scales, but showed poorer hydrological abilities for capturing flood peaks, comparable with the gauge-based simulation. Model recalibration by using SREs effectively enhanced the hydrological performance.

Table 1. *Cont.*

Study	Data (Resolution)	Hydrological Model	Catchment (Area)	Major Findings
Jiang et al. (2018) [104]	IMERG-E, IMERG-L, and IMERG-F (V05, 0.5 h, 0.1°), TRMM 3B42V7 and 3B42RT (3 h, 0.25°)	Xinanjiang model	Mishui basin, a tributary of the Xiangjiang River (9972 km^2)	IMERG-F performed visibly better than 3B42V7 and both IMERG-E and IMERG-L demonstrated a better performance than 3B42RT for hydrological simulations. However, the simulated streamflow using SRE was less accurate than simulations using rain gauge observations. Model recalibration using SREs obviously improved hydrological performance for the whole simulation period and flood season.
Jiang et al. (2019) [73]	IMERG-F and IMERG-E (V05, 0.5 h, 0.1°), TMPA 3B42V7 (3 h, 0.25°)	HBV model	300 small to medium-sized catchments across Mainland China (<5000 km^2)	Models forced with IMERG-E and IMERG-F performed well as those forced with gauge-based precipitation in most cases, and much better than those forced with TMPA 3B42V7. However, there were region-specific discrepancies (e.g., much better model performance in humid regions).
Deng et al. (2019) [74]	The latest GSMaP_Gauge (GG) data (1 h, 0.1°)	SWAT model	Hanjiang River basin (159,000 km^2)	The corrected GG produced a better performance of runoff simulation with a maximum increase of 11.94% and 6.1% in NSE and R^2, respectively, compared to GG.
Lai et al. (2019) [82]	CHIRPS and PERSIANN-CDR (daily, 0.25°)	GXAJ model	Beijiang River basin (38,672 km^2)	Both SREs presented acceptable performance for hydrological modeling, and CHIRPS outperformed PERSIANN-CDR. After recalibration, the hydrological performances were obviously improved for both SREs.
Zhang et al. (2019) [17]	TMPA 3B42V7 (3 h, 0.25°)	Xinanjiang model and Tank model	Yangtze River basin (1,800,000 km^2)	The adjusted TMPA 3B42V7 data improved the accuracy of hydrological simulation more than the original 3B42V7 data, which was comparable to rain-gauge observations, but both of them performed poorly for the peak runoff prediction.
Su et al. (2019) [102]	IMERG-E, IMERG-L, and IMERG-F (V05, 0.5 h, 0.1°)	VIC model	Huaihe River basin (16,000 km^2)	IMERG-F displayed an acceptable performance in long-term streamflow simulations, while IMERG-E and IMERG-L exhibited little potential hydrologic utility. All three IMERG products were obviously overestimated in short-term flooding and were clearly underestimated in long-term flooding. None of them performed better than dense gauge observations in hydrologic utility.

Abbreviations: SAC-SMA, Sacramento Soil Moisture Accounting model; VIC, Variable Infiltration Capacity; VIC-3L, the three-layer VIC; TAMSAT, Tropical Applications of Meteorology using SATellite data; TAMSAT CCD, the cold cloud duration using TAMSAT data; CPC-FEWS, Climate Prediction Center/Famine Early Warning System; WBL, water balance error; RMSE, root-mean-square error; CREST, Coupled Routing and Excess Storage; TAMSIM, TAMSAT Simulation; PERSIANN-CDR, PERSIANN–Climate Data Record; HLRDHM, Hydrology Laboratory Research Distributed Hydrologic Model; CHIRPS, Climate Hazards Group InfraRed Precipitation with Station data; CMORPH CRT, CMORPH bias-corrected product; CMORPH_BLD, CMORPH satellite-gauge blended product; CMORPH CMA, CMORPH satellite–gauge merged product developed at the National Meteorological Information Center (NMIC) of the China Meteorological Administration (CMA); MGB-IPH, Large Scale Basins Model of Brazilian Institute of Hydraulic Research; IMERG-E, the near-real-time “Early” run of IMERG; IMERG-L, the near-real-time “Late” run of IMERG; IMERG-F, the post-real-time “Final” run of IMERG; CMORPH_RAW, CMORPH raw satellite-only precipitation product; R^2, coefficient of determination; SIMEPAR, Paraná Meteorologic System; MHD-INPE, Modelo Hidrológico Distribuído of Brazilian Institute for Space Research; SREM2D, the 2-Dimensional Satellite Rainfall Error Model; GLDAS, Global Land Data Assimilation System; GSMaP-MVK+, GSMAP moving vector with Kalman filter; APHRODITE, Asian Precipitation-Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources; WEBDHM, Water and Energy Budget-based Distributed Hydrological Model; TOPMODEL, TOPography based hydrological MODEL; MPEG, Multi-sensor precipitation estimate-geostationary; HBV, Hydrologiska Byråns Vattenbalansavdelning; SM2RAIN$_{CCI}$, the derived rainfall obtained by applying SM2RAIN to the European Space Agency Climate Change Initiative Soil Moisture (ESA CCI SM) products; MISDc, Modello Idrologico Semi-Distribuito in continuo; GSMaP_Gauge, a product that adjusts the GSMaP_MVK estimate with global gauge analysis supplied by the National Oceanic and Atmospheric Administration (NOAA).

3.2. *Remotely Sensed Evapotranspiration*

Evapotranspiration (ET) is a major component of the water and energy exchanges among the atmosphere, hydrosphere, and biosphere [107,108]. Integrating actual ET (ET_a) data into hydrological models makes it possible to improve hydrological modeling, especially for highly regulated basins (Table 2). For example, Immerzeel et al. (2008) [25] successfully calibrated the SWAT model using the remotely sensed derived ET in the upper Bhima catchment (45,678 km^2), where streamflow was mainly human controlled. The correlation coefficient between the monthly sub-basin simulated and measured ET_a increased from 0.40 to 0.81. Hartanto et al. (2017) [31] assimilated the satellite-based ET_a into a distributed hydrological model at a controlled water system. Their results showed that the modelled cumulative discharge was improved, with the bias decreasing from 14% to 4%.

In general, there are few studies on the application of satellite-based ET_a data to enhance streamflow simulations, and most of them are limited to larger catchments (Table 2). On the one hand, ET_a is a non-state variable in hydrological models, which cannot achieve assimilation feedback for the model and update model state variables when data assimilation methods are used to combine ET_a with hydrological models [109]. Hence, the hydrological models cannot be optimized as a whole. This restricts the application of ET_a observations in most hydrological models, in which, inversely, state variables (e.g., soil moisture) are used for the ET_a estimate. Certainly, if the time response relationship between ET_a and state variables were well established, the model optimization and more accurate hydrological estimates could be obtained [109,110]. For example, Zou et al. (2017) [108] established the time response relationship between ET_a and soil moisture using a nonlinear soil water availability function based on logistic distribution, which achieved more accurate results for ET_a, as well as streamflow and soil moisture. However, it is noteworthy that most hydrological models show no explicit time response relationship between ET_a and the state variable (e.g., soil moisture). Thus, it is hard to effectively convert ET_a into a state variable for realizing the direct assimilation and achieving assimilation feedback on state variables [108,110]. Moreover, soil moisture conversion functions may vary in their soil wetness and leaf-area index [108,111,112]. In this respect, further studies are expected to be conducted to improve both ET_a estimation and other model predictions, especially in the small and middle watersheds.

On the other hand, ET_a is inherently difficult to be measured and predicted, but an accurate ET_a is critical for its application in hydrological modeling. Many researchers have been making great efforts in ET_a estimation, particularly using remote sensing methods, because of the relatively contiguous measurements for surface biophysical variables affecting ET at regional to global scales. Zhang et al. (2016) [113] summarized existing major remote sensing ET_a estimation methods, as well as their uncertainties and limitations, and provided a perspective on the future development of these methods. Improvement in satellite-based remote sensing in the future will enhance our capability to monitor global water and energy cycles [113]. Accordingly, satellite-based ET_a data would make greater contributions to the improvement of hydrological predictions.

Table 2. Relevant studies on improving hydrological simulations using satellite-based ET_a.

Study	ET_a Estimation Method	Data (Resolution)	Hydrological Model	Catchment (Area)	Major Findings
Immerzeel et al. (2008) [25]	SEBAL	MODIS (250 m, monthly)	SWAT model	Upper Bhima catchment (45,678 km^2)	Significantly improved ET_a estimates. Modelled discharges were well within one standard deviation of the observed data.
Pan et al. (2008) [114]	SEBS	MODIS (5 km, daily)	VIC model	Red-Arkansas River Basin (645,000 km^2)	Obtained the probabilistically optimal ET estimates, but was unable to improve other model predictions (e.g., soil moisture and streamflow).
Qin et al. (2008) [115]	SEBS	MODIS (1 km, monthly)	WEP-L model	Huai River Basin (317,800 km^2)	Obtained more accurate ET estimates, but contributed little to the estimated water budget terms (e.g., soil moisture and streamflow)

Table 2. *Cont.*

Study	ET_a Estimation Method	Data (Resolution)	Hydrological Model	Catchment (Area)	Major Findings
Rientjes et al. (2013) [42]	SEBS	MODIS (1 km, daily)	HBV model	Karkheh River Basin (51,000 km^2)	Produced satisfying estimates for both streamflow and ET_a and reproduced the catchment water balance through the multi-variable calibration of streamflow and satellite-based ET_a, compared to the single-variable calibration, which provided poor simulation performance for the second variable (streamflow or ET_a) and poor reproduction of the water balance.
Zou et al. (2017) [108]	Improved ET algorithm by Mu et al. 2011 [116]	MOD16A2 ET_a data (1 km, 8-day)	DTVGM model	Upper Huai River Basin (30,630 km^2)	Improved the accuracy of spatiotemporal variations of ET_a and the simulation performance of both soil moisture and streamflow.
Hartanto et al. (2017) [31]	The ITA-MyWater algorithm	MODIS (250–500 m, 8-day)	SIMGRO model	Rijnland area (1200 km^2)	Improved the discharge modeling and reduced the bias of simulated cumulative discharge to the observed data from 14% to 4%.
Herman et al. (2018) [117]	SSEBop model and ALEXI model	MODIS (1 km, 8-day), remotely sensed land surface temperatures (4 km, daily)	SWAT model	Honeyoey Creek-Pine Creek Watershed (approximately 1100 km^2)	Improved ET_a estimations when maintaining the performance of streamflow estimates through multi-variable calibration using ET_a and streamflow, compared with the GA calibration using ET_a alone, which produced better ET_a simulations but lowered streamflow calibrations. Produced better ET_a estimations via the calibration based on the SSEBop's ET_a dataset compared to the ALEXI dataset.

Abbreviations: SEBAL, Surface Energy Balance Algorithm for Land; MODIS, Moderate Resolution Imaging Spectrometer; SEBS, Surface Energy Balance System; WEP-L, Water and Energy transfer Process in Large river basins; MOD16, MODIS global evapotranspiration product; DTVGM, Distributed Time-Variant Gain Model; ITA-MyWater algorithm, Integrated Thermodynamic Algorithms for MyWater project, which is an adaptation of SEBAL; SIMGRO, SIMulation of GROundwater and surface water levels; SSEBop, Simplified Surface Energy Balance; ALEXI, Atmosphere-Land Exchange Inverse; GA, Genic Algorithm.

3.3. Remotely Sensed Soil Moisture

Soil moisture, interacting with surface water and groundwater, affects a variety of hydrological processes [118–122]. It controls the partitioning of rainfall into infiltration and runoff, subsequently controlling water movement and baseflow generation from the soil profile and determining streamflow and flooding [15,29,118,123,124]. The integration of soil moisture information into hydrological models has the potential to enhance hydrological modeling predictability [21,39,40,118,121,125–127] (Table 3). Although limited improvement in streamflow simulations has been produced in a small watershed, which has better in-situ observations, by coupling soil moisture data, the performance of the runoff prediction in the presence of larger errors in precipitation observations [123] and flood predictions [45,126,128] showed a significant improvement. In watersheds which have no available data, data scarcity, transient rivers, man-controlled runoff, large scales, semi-arid or arid climates, soil moisture data demonstrate the importance in achieving more accurate streamflow estimates [21,39,45,118,123,129–131].

Commonly, soil moisture monitoring can be obtained from in situ and satellite observations. In situ measurements can provide accurate soil moisture information over the entire root zone for hydrological modeling, but they represent soil moisture conditions only over a small spatial scale and are unable to characterize the spatial heterogeneity and variability of soil moisture over a large scale [118,122,132,133]. Satellite-based remote sensing can provide an alternative to develop observations for soil moisture with a large range and high accuracy, which can fill in gaps with sparse ground measurements or poor spatial representativeness [121,122,126,132,134]. Among these techniques, microwave remote sensing (passive and active) has been widely applied for the retrieval of global soil moisture [135], because microwave sensors are not limited by cloud cover and nighttime conditions [122]. In contrast to active sensors, passive microwave sensors, like the Soil Moisture and Ocean Salinity (SMOS), Advanced Microwave Scanning Radiometer for EOS (AMSR-E), and the Soil Moisture Active Passive (SMAP), have a more mature algorithm for surface soil moisture inversion and a larger soil penetration depth. However, they are less sensitive to the influence of vegetation structure, surface roughness, snow cover, frozen soil, and precipitation events due to their poor spatial resolution [15,122]. Active microwave sensors, such as the Advanced Scatterometer (ASCAT), have higher spatial and temporal resolutions and a better accuracy because of less radiofrequency interference, but they have a lower soil penetration depth (0.5–2 cm) [15]. Early studies concluded that passive microwave products were more reliable over bare to sparsely vegetated regions, but their performance decreased with increasing vegetation density [136]. In contrast, active microwave products performed better over moderately vegetated regions [137]. However, neither satellite products can provide accurate soil moisture estimates over dense vegetation cover [136,138].

Some researchers investigated the influence of different satellite soil moisture products on hydrological predictions. For example, Laiolo et al. (2016) [20] concluded that assimilating the H07 (surface soil moisture product over Europe and North Africa with a spatial resolution of 25 km) and H14 products (soil moisture profile index in the root region by scatterometer data assimilation with a 25 km resolution) derived from ASCAT observations in the Satellite Application Facility on Support to Operational Hydrology and Water Management (H-SAF) project provided the greatest benefits to the discharge model predictions. However, the assimilation of SMOS only produced a weak improvement of the model's performance due to the few data available and the data quality (43 km average resolution). The H08 product, which was disaggregated and re-sampled from H07 at fine scale (1 km) for hydrological applications, did not obtain better results than H07. This suggested that the disaggregation process did not bring benefits. Patil and Ramsankaran (2018) [124] found that in the Wyara catchment of India (1650 km^2), the SMOS observations obtained better assimilation efficiency than ASCAT observations, but the opposite result was found in for the Varada catchment of India (5092 km^2). Generally, the impact of different satellite soil moisture products on streamflow simulations is rarely compared. More attention has been paid to assessing the accuracy of remote sensing estimates of soil moisture at regional or global scales.

In addition, it should be noted that remotely sensed soil moisture products can only provide an estimate of soil moisture in the top few centimeters (~5 cm) of the profile [123]. Therefore, the application of these products has focused on surface runoff and storm-related flooding type events. However, the subsurface and root-zone soil moisture have a more significant effect on runoff simulation [123,127,139]. Several studies explored the potential of surface soil moisture estimates to update subsurface soil moisture in hydrological modeling using data assimilation techniques [21,124]. For instance, Patil and Ramsankaran (2017) [21] assimilated satellite-based soil moisture into the SWAT model in the Munneru catchment and found that perturbing the field capacity of soil can significantly improve the coupling between the surface and subsurface layers, despite producing moderate improvement in streamflow estimates. Subsequently, Patil and Ramsankaran (2018) [124] coupled the Soil Moisture Analytical Relationship (SMAR) into the SWAT model to update the sub-surface soil moisture at the Wyra river catchment and Varada catchment in India. They found that this scheme could produce a better improvement in surface flow, groundwater flow, and streamflow estimates. However, the improvement in streamflow simulations was still moderate, because updating the soil moisture alone could insufficiently remedy the errors in streamflow simulations, that originated from erroneous model forcing in subsequent days. In order to get the root zone soil moisture information, Wanders et al. (1999) [140] proposed the Exponential Filter method based on the surface observations of satellite products. Some researchers, such as Brocca et al. (2012) [139] and Massari et al.

(2015) [29], applied this approach to estimate the soil water index of the root zone and then assimilated it into the hydrological model to improve discharge predictions.

In general, coupling remote sensed soil moisture data into hydrological models can be beneficial for hydrological predictions. However, simulation performance is affected by a variety of factors, including the selected hydrological model [15,49], catchment characteristics [15,29,141], data availability [47,141], assimilation or calibration procedure [40,46,50,120,125,142,143], as well as the rescaling technique of satellite products [15,20,29,126]. As mentioned above, data assimilation and model calibration are expected to improve hydrological modeling in different ways [50]. Koster et al. (2018) [50] compared the data assimilation and model calibration in contributions to hydrological estimation by integrating SMAP soil moisture data into a land surface model. Their results showed that 1) two approaches were distinct and largely complementary in contributions to simulations of both streamflow and soil moisture; 2) data assimilation improved streamflow timing and reduced the unbiased RMSE (ubRMSE) of soil moisture estimates, while model calibration reduced the model biases in both streamflow and soil moisture; and 3) the joint use of two approaches provided the highest soil moisture simulation accuracy. Consequently, data assimilation and model calibration demonstrate their own advantages in streamflow predictions. However, overall, data assimilation has gained more applications in incorporating remotely sensed soil moisture products into hydrological models for better model performance (Table 3).

Table 3. Relevant studies of the applied satellite-based soil moisture data for improving hydrological simulations.

Study	Satellite Data Used (Resolution)	Method	Assimilated/ Calibrated Observations	Hydrological Model	Catchment (Area)	Major Findings
Pauwels et al. (2001) [144]	The first and second ERS (about 50 km, 35-day)	Statistical correction assimilation method	Surface soil moisture	Lump and distributed versions of TOPLATS	Zwalm watershed of Belgium (114.3 km^2)	Improved discharge predictions.
Crow and Ryu (2009) [145]	AMSR-E (about 40 km, 1–2 day)	A smoothing framework (EnKF and EnKS)	Surface soil moisture	Sacramento hydrologic model	–	Improved both pre-storm soil moisture conditions and streamflow predictions, especially for high flow events.
Matgen et al. (2012) [126]	ASCAT (25 km, bi-daily)	Particle filtering technique	ASCAT-derived SWI and in situ soil moisture	BibModel	A well-gauged Bibeschbach experimental catchment in Luxembourg (10.8 km^2)	Significantly improved both discharge and soil wetness forecasts by the assimilation of in situ soil moisture data but produced a negative or small positive impact when assimilating ASCAT-based SWI data.
Brocca et al. (2012) [139]	ASCAT (25 km, daily)	EnKF	Surface and root-zone soil moisture	MISDs model	Niccone catchment in Central Italy (137 km^2)	Achieved a great improvement in discharge prediction, particularly for the floods occurring during dry to wet transition periods through the assimilation of the RZSM product, compared to the assimilation of surface soil moisture, which produced a small effect on runoff simulations.
Brocca et al. (2013) [141]	ASCAT (25 km, daily), AMSR-E (25 km, daily), ECMWF (80 km, daily)	Nudging technique	Surface and root-zone soil moisture	MISDs model	Six catchments in different four countries	Improved runoff prediction for the assimilation of three soil moisture products, but the assimilation performance was remarkably impacted by the accuracy of the satellite soil moisture retrievals, the length of the observation period, and the catchment's climatic conditions.

Table 3. *Cont.*

Study	Satellite Data Used (Resolution)	Method	Assimilated/ Calibrated Observations	Hydrological Model	Catchment (Area)	Major Findings
Wanders et al. (2014) [45]	ASCAT (25 km, daily), AMSR-E (about 40 km, daily), SMOS (about 43 km, daily)	EnKF	Surface soil moisture, streamflow	LISFLOOD model	Upper Danube Basin in Bratislava (135,000 km^2)	Improved flood forecasting, with the CRPS increasing by 5%–10% on average when assimilating remotely sensed soil moisture, especially in combination with more discharge observations.
Sutanudjaja et al. (2014) [39]	The SWI product derived by Wanger et al. 1999 [140] based on RS Scatterometer (about 50 km, 10-day)	A multiobjective and stepwise calibration approach	Discharge observations and SWI in the topsoil layer (0–20 cm)	PCR-GLOBWB model	Rhine–Meuse basin (about 200,000 km^2)	Yielded acceptable accuracy for discharge and soil moisture simulation, as well as predicting groundwater head dynamics through the combined calibration to discharge and remotely sensed SWI data.
Massari et al. (2015) [29]	ASCAT and H25 SM-OBS-4 product from the H-SAF project (25 km, daily)	EnKF	Surface and root-zone soil moisture	MISDc model	Five sub-catchments of the Upper Tiber River basin in Central Italy (137–2040 km^2)	Improved discharge predictions (with a mean efficiency of about 30%); examined the effect of catchment area, soil type, climatology, rescaling technique, observation, and model error selection of the assimilation results.
López et al. (2016) [46]	AMSR-E (downscaled from ~0.5° to 0.08°, daily)	EnKF	Surface soil moisture, streamflow	Local OpenStreams wflow_sbm model and global PCR-GLOBWB model	Murrumbidgee River basin in Australia (84,000 km^2)	Produced the largest improvement of streamflow estimates via assimilation of soil moisture; further improved simulated streamflow (20% reduction in RMSE) with jointly assimilated streamflow and downscaled soil moisture observations.
Yan and Moradkhani (2016) [120]	ASCAT (25 km, daily)	PF-MCMC method	Surface soil moisture, streamflow	SAC-SMA model	A sub-watershed of Salt River basin in Arizona (7 379 km^2)	Improved the surface soil moisture prediction and guaranteed the accuracy of streamflow prediction when jointly assimilating streamflow and soil moisture inferred from geostatistical modeling, compared to the assimilation of the outlet streamflow only.
Montero et al. (2016) [47]	SM product H14 (25 km, daily), SCA product H10 (1–5 km, daily) and SWE product H13 (0.25°, Daily/weekly) from H-SAF project	Variational assimilation approach	Streamflow data as well as remotely sensed SM, SCA and SWE	HBV model	Two head catchments in Germany (1468 km^2, 2419 km^2) and the headwaters of Euphrates Basin in Turkey (10,275 km^2)	Produced a slight reduction in the streamflow forecast skill but a significant improvement in the forecast skill of soil moisture when assimilating H-SAF observations, compared to the assimilation of streamflow solely.
Laiolo et al. (2016) [20]	Three H-SAF products (25 km or 1 km, daily), and SMOS product (43 km average, daily)	Nudging technique	Surface soil moisture	Continuum model	Orba watershed in Italy (800 km^2)	Achieved a general improvement of discharge predictions even using a simple assimilation technique; increased NSE from 0.6 to 0.7; reduced errors on discharge up to the 10%.
Patil and Ramsankaran (2017) [21]	SMOS L3 product (25 km, daily)	EnKF	Surface soil moisture	SWAT model	Munneru river catchment of India (10,156 km^2)	Significantly improved the vertical coupling of soil layers in the SWAT model, but produced the moderate enhancement in simulated streamflow due to the limitations in SWAT model in reflecting the profile soil moisture updates in surface runoff computations.

Table 3. *Cont.*

Study	Satellite Data Used (Resolution)	Method	Assimilated/ Calibrated Observations	Hydrological Model	Catchment (Area)	Major Findings
Zhang et al. (2017) [48]	Not clear soil moisture data, possibly from SMOS and SMAP	EnKF	Soil moisture, SWE, and discharge	SWATGP model	Babaohe River Basin of China (2455 km^2)	Improved the estimates of hydrological states by the presented SWAT-HDAS system using soil moisture/snow/discharge observation data, but the application of soil moisture and SWE observations may degrade streamflow estimates when discharge observations have been assimilated.
Patil and Ramsankaran (2018) [124]	SMOS (0.25°, daily) and ASCAT (0.25°, daily)	EnKF	Surface and root zone soil moisture	SWAT model	Wyra catchment (1650 km^2) and Varada catchment (5092 km^2) in India	Moderately improved surface runoff, lateral flows, groundwater flows, and streamflow using the proposed SMAR-EnKF scheme for updating profile soil moisture.
Loizu et al. (2018) [15]	ASCAT product (25 km, daily)	EnKF	Surface soil moisture (SSM)	MISDc and TOPLATS model	Nestore catchment (725 km^2) and Arga catchment (810 km^2) in Spain	Improved simulated streamflow, which NSE increased by 10%–45% from the validation run and 6%–35% from the open-loop simulation, with the variation depending largely on the catchment characteristics, the assumed SSM observation error, and the selected re-scaling technique.
Li et al. (2018) [40]	SMOS (~45 km, 1-3 day)	A joint calibration scheme	Gauged streamflow and near-surface soil moisture	GRKAL model	Clarence River catchment upstream of Lilydale and Condamine River catchment upstream of Chinchilla in Australia	Compared with streamflow only calibration, it slightly degraded the streamflow simulation at gauged sites during the calibration period but obtained improvements at the same gauged sites during the independent validation period and a more consistent and statistically significant improvement at the gauged sites, which were not used in the calibration.
Leach et al. (2018) [49]	SMOS-SM data (43 km, daily) and SNODAS-SWE data (1 km, daily)	EnKF	Soil moisture, SWE and streamflow observations	GR4J, HYMOD, MAC-HBV, and SAC-SMA models	Highly-urbanized Don River basin in Canada (350 km^2)	Produced some improvement to different aspects of hydrologic simulation and forecasting when jointly assimilating soil moisture and SWE.

Abbreviations: ERS, European Remote Sensing Satellites; TOPLATS, TOPMODEL-based Land-Atmosphere Transfer Scheme; EnKF, ensemble Kalman filter; EnKS, ensemble Kalman smoother; SWI, Soil Water Index; BibModel, a numerical model which incorporates the dominant hydrological processes in the Bibeschbach catchment; MISDc, Modello Idrologico Semi-Distribuito in continuo; RZSM, root-zone soil moisture; ECMWF, European Centre for Medium-Range Weather Forecasts; Six catchments, included two catchments in central Italy (Niccone, 137 km^2 and Assino,165 km^2), one in South Italy (Fiumarella, 33 km^2), one in Luxembourg (Bibeschbach, 12 km^2), one in France (Valescure, 3.7 km^2), and one in US (Lucky Hills, 0.001 km^2); LISFLOOD, a GIS-based distributed model for river basin scale water balance and flood simulation; CRPS, continuous ranked probability score; PCR-GLOBWB, PCRaster Global Water Balance; PF-MCMC, Particle Filter-Markov Chain Monte Carlo method; SM, soil moisture; Three H-SAF products, included SM OBS 1-H07 (25 km), SM OBS 2–H08 (1 km) and SM DAS 2–H14 (25 km), which were derived from ASCAT observations; SCA, snow covered area; SWE, snow water equivalent; SWATGP, a gridded and parallelized SWAT model [146]; SWAT-HDAS, integration of the gridded and parallelized SWAT model (SWATGP) and the Parallel Data Assimilation Framework (PDAF); SMAR-EnKF, SMAR was used for estimating root zone soil moisture from surface measurements, coupled with EnKF; GRKAL, a new version of GRHUM, which two independent near-surface and root-zone soil moisture layers are parameterized and the drainage from the near-surface layer is used as the input for the root-zone layer; GRHUM, the soil water storage of the GR4J reparametrized into a two layer system of the near-surface soil moisture layer and the bulk soil moisture layer; GR4J, modèle du Génie Rural à 4 paramètres Journalier; SNODAS, Snow Data Assimilation System; HYMOD, HYdrologic MODel; MAC-HBV, McMaster University–HBV.

3.4. Remotely Sensed Snow Observations

In mid-altitude and high-altitude catchments, snowmelt can contribute largely to runoff, owing to its influences on water storage and surface albedo [147–149]. Snowmelt accounts for about 70%–80% of the total annual runoff in such regions of the northern United States [150]. Therefore, the accurate estimate of snowmelt is important for streamflow predictions in these regions, especially in mountainous areas [149,150]. Some studies have shown that assimilating snow observations, such as SWE, Snow Depth (SD), and SCA, into a hydrologic model could achieve improved streamflow estimates [151–156]. This improvement was more notable in poorly calibrated basins than basins with a relatively higher calibrated model performance [154].

In recent years, remotely-sensed snow observations have been increasingly taken account for streamflow estimates in snow-dominated areas because of their increasing spatial resolution, reasonable spatiotemporal continuity, and relatively short latency [155]. SCA can be measured using optical sensors, such as Advanced Very High Resolution Radiometer (AVHRR), MODIS, and the Interactive Multisensor Snow and Ice Mapping System (IMS), which have high spatial resolutions [157]. These sensors can exploit the high reflectance of snow-covered areas in comparison with areas without snow cover but are limited to cloud-free conditions [158,159]. Active microwave sensors, such as RADARSAT Synthetic Aperture Radar (SAR), ENVironmental monitoring SATellite Advanced SAR (Envisat ASAR), and Terra SAR-X, can also detect snow-cover characteristics, but they are only able to reliably recognize wet snow [157,160]. SD or SWE can be retrieved via microwave technologies, especially passive microwave (PM) sensors, such as Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave Imager (SSM/I), and AMSR-E [55,161]. Compared with active sensors, PM sensors have a coarser spatial resolution and lower accuracy in regions with dense vegetation cover and proximity to open water. They are also prone to signal saturation in regions with deep snowpacks but can produce accurate observations under cloudy and nighttime conditions [159,162].

Assimilating these satellite-based snow observations can potentially lead to improved snow predictions and improved streamflow predictions (e.g., [151,156]). However, this improvement is limited mainly to the snowmelt season [147,153]. Moreover, some studies have reported that snow data assimilation had limited success for streamflow simulations (e.g., [47,161,163]). For example, Kumar et al. (2014) [161] found that the assimilation of SD datasets from SMMR, SSM/I, and AMSR-E, which was augmented with in situ meteorological station-based measurements, improved the snow fields but did not always translate to corresponding improvements in streamflow. This was mainly caused by the low skill of PM-based retrievals, as mentioned above [161,162]. Bergeron et al. (2016) [153] reported that the assimilation against SCA data from MODIS yielded little or no improvement for all state variables and even a strong deterioration in most cases, compared to the open-loop scenario. The most probable factor for this result was the absence of SCA as a state variable or a proxy with a great enough linear relationship to SCA [153].

In light of the unsatisfactory results obtained from assimilating the single snow variable, there are studies on integrating multi-source or multi-variable snow observations to improve streamflow predictions. For instance, Kumar et al. (2015) [159] examined the approach of using SCA observations from MODIS and IMS as additional snow detection constraints in PM-based SD data assimilation. Their results showed that the SCA-based constraint, especially with the use of MODIS datasets, not only effectively improved estimates of snow depth, but also enhanced simulated streamflow, despite only small improvements. Liu et al. (2015) [155] found that the integration of SD data from AMSR-E, and in-situ observations from the Snow Telemetry (SNOTEL) networks located at high altitudes, along with the terrain aspect, could improve snow predictions and produce reliable streamflow predictions. Incorporating SCA data from MODIS could further improve the streamflow results slightly [155].

In addition, some studies have explored the effect of the joint assimilation of snow and other variables (e.g., streamflow, soil moisture) on the performance of streamflow predictions. Leach et al. (2018) [49] found that the assimilation of remote-sensed soil moisture and SWE data into different hydrological models improved hydrologic modeling and forecasting in the highly-urbanized Don

River basin (350 km^2). However, a study by Montero et al. (2016) [47] showed that the assimilation of soil moisture, SWE, and SCA from H-SAF observations slightly reduced the streamflow forecast skill compared to the assimilation of streamflow data alone. To sum up, snow data has a limited ability to enhance streamflow estimates, but an improved state of SWE may contribute more accurate information for the available water for the snowmelt, which is crucial for runoff prediction during the snowmelt season [152].

3.5. Remotely Sensed TWSC Data

Remotely sensed TWSC from GRACE have been also used to improve hydrological modeling (e.g., [53,164,165]). For instance, Chen et al. (2017) [53] reported that the joint application of remotely sensed SCA, SWE, and TWSC, with streamflow observations in the hydrological model's calibration, provided more reliable streamflow, snow (both SCA and SWE), and TWSC simulations than the calibration based on streamflow and/or SCA performance. However, several studies have demonstrated that the improvement in streamflow estimates using GRACE-derived TWSC data was modest rather than significant (e.g., [164,165]). In addition, some studies showed that the GRACE assimilation could not enhance or might even degrade the performance of streamflow simulations [41,166,167]. For instance, Bai et al. (2018) [41] discovered that incorporating GRACE data into the model calibration, along with the runoff observations, achieved more reliable TWSC and ET simulations but slightly reduced the accuracy of streamflow simulations compared to the traditional single-objective calibration. Overall, GRACE-derived TWSC data show great limitations in improving hydrological simulations, especially in small catchments, as these data cannot help to capture high flow events because of their coarse temporal and spatial resolution (monthly, $1^\circ \times 1^\circ$ respectively) [167,168]. Nevertheless, these data can still provide candidate complementary data to better constrain parameterizations of hydrological models in conjunction with streamflow observations [41].

3.6. Remotely Sensed Land Surface Temperature

Land Surface Temperature (LST) is the connection between water and energy balances. LST derived from polar orbiting or geostationary satellites can be used to calibrate the hydrological model [44]. Moreover, the calibration procedure based on satellite-based LST alone may outperform the calibration based on discharge [169]. However, most studies reported that calibrations against satellite-derived LST data, evenly combined with streamflow observations, produced poorer performance for streamflow simulations [44,170,171]. Probably, the application of LST is more suitable for large-scale catchments [169,170]. Nevertheless, LST can be helpful to constrain model parameters in the calibration process and reduce parametric uncertainty, compared to streamflow only calibration [44,170,171].

3.7. Remotely Sensed River Width

In ungauged basins lacking any ground observations, satellite observations of river width can be used as a surrogate to represent streamflow variations and be applied to hydrological model calibration [172]. Even river discharge can be estimated exclusively using satellite-derived parameters (e.g., river width, water depth, flow velocity) [173–176]. For example, Gleason and Smith (2014) [174] proposed a satellite-only AMHG (at-many-stations hydraulic geometry) discharge retrieval method. This method, based solely on Landsat Thematic Mapper images observations of instantaneous river surface width, yielded river discharge agreeing to within 20%–30% of in situ observations. Moreover, the AMHG method can also address global discharge knowledge gaps solely from repeat satellite imagery [175]. Overall, promising results of streamflow retrievals from satellite observations of river hydraulic variables have been reported in large continental rivers with river widths exceeding 100 m. However, they have not been applied to smaller regional rivers. More importantly, satellite-based streamflow retrievals cannot achieve the accuracy of in situ observations and should not be treated as a gauge replacement strategy [176–178].

4. The Application of Data Assimilation for Merging Satellite-Based Remote Sensing with a Hydrological Model

Data assimilation (DA) techniques have been widely and increasingly applied in hydrological studies [108,119,120,125,130,179]. Particularly, DA shows superiority in integrating multiple observation types into hydrological models [45,46,49,120,121]. DA can not only update the hydrological state variables and model parameters (simultaneously seeking the best model state and parameters to enhance model performance) but also can account for and reduce various sources of uncertainties in both the models and the assimilated data products [21,49,108,179,180]. Some studies have indicated that, overall, the assimilation of observed data, even poor or coarse data, could produce at least a slight improvement compared to the open-loop run (no DA) [20,21,130,181–183].

Early studies of data assimilation in hydrology focused on the application of soil moisture in land surface models [119,184–186]. Further, streamflow or ET_a data have been assimilated into hydrological models, offering promising results [108,119,187,188]. Recently, the potential of observed data such as SWE, SCA, and TWSC in hydrological predictions has been investigated, illustrating both positive and negative results [148,153,154,164,166]. In addition, multiple observation data types have been also assimilated into hydrological models, thereby achieving better performance in model predictions [32,46,119,121,189]. For instance, Yan and Moradkhani (2016) [120] found that the joint assimilation of remote-sensing surface soil moisture and streamflow significantly reduced RMSE relative to the assimilation of the outlet streamflow solely. Xiong et al. (2019) [32] demonstrated that the time-varying model parameters (evapotranspiration parameter and water storage capacity) gained by adding ET_a data into the assimilation with streamflow resulted in a significant improvement in deterministic streamflow and ET simulation, compared to the separate assimilation of streamflow, with time invariant approaches.

The main data assimilation techniques used to combine remotely sensed data with hydrological models include the Kalman filter and its variants, particle filters (PF), and variational methods [15,119]. Each technique has its own advantages and weaknesses [190,191]. Among them, the ensemble Kalman filter (EnKF) is the most widely used technique in hydrology [21,48,108,119,121,142,179,185,192], because it can not only account for nonlinearities (and partially nonGaussianity) with few restrictive assumptions [119,188], but can also continuously update hydrological state variables and parameters when new measurements are available with simple implementation [108,119]. It can also flexibly represent various uncertainties in simulations and observations [21,28,119]. However, EnKF assumes a Gaussian distribution in model errors, which may lead to degeneration when the size of the state space is much larger than the ensemble size [119,121]. In addition, the stationary parameter assumption within EnKF is challenged under climate and land use change [120,193,194]. These deficiencies may weaken the superiority of EnKF [120,179,195,196]. In contrast, Particle Filters (PFs) can relax the Gaussian assumption of error distributions [120,179,191] and more completely represent state/parameter posterior distribution for a given nonlinear and non-Gaussian system [120,179]. Hence, PF is considered to be a more robust DA technique for hydrological studies [120,180,196–198] and has received increasing attention as an effective tool to improve model predictions [179]. However, PF commonly requires more samples than other DA methods and, hence, may impose an obvious computational burden for achieving accurate results [191,199]. Besides, PF shows one potential limitation in terms of the particle degeneracy that the particles lose their ability to correctly approximate the posterior distribution [179].

Given these concerns, some researchers have explored new assimilation schemes based on popular DA techniques for better assimilation performance [48,125,179,191,200]. For example, Andrieu et al. (2010) [200] proposed the PF-MCMC technique to reduce weight degeneracy within the PF. Then, Abbaszadeh et al. (2018) [179] presented the Evolutionary PF-MCMC (EPFM) to characterize a more accurate and reliable posterior distribution for state variables of interest in data assimilation applications. Meng et al. (2017) [125] established an effective data assimilation scheme based on the Ensemble Kalman Filter and Smoother (named EnKF-S) by accounting for the runoff routing lag between streamflow and soil moisture, which has been rarely considered in most studies. To overcome the shortcomings in EnKF and PF, Fan et al. (2017) [191] developed two integrated data assimilation schemes, i.e., the coupled EnKF and PF (CEnPF) and parallelized EnKF and PF (PEnPF) approaches, which provided better results for both deterministic and probabilistic predictions than traditional EnKF and PF approaches. Overall, these new DA methods have made contributions to obtain better hydrological predictions. However, their practicability and feasibility also need further verification.

In additional, it should be noted that the unconstrained implementation of DA to the model output may result in model states beyond physically realistic limits, and, conversely, physical limits can be controlled by using constraints [28,142,201,202]. Hence, a strongly-constrained (SC) DA approach has been proposed to account for errors in the model's initial and boundary conditions, as well as model parameters to improve the fit of the model to the observations [203]. However, this SC DA approach ignores the model error, and, hence, updated states may be over-adjusted in order to compensate for model errors [142,167]. In contrast, a weakly-constrained (WC) DA approach has been developed, which can account for model structural errors with less adjustment to state variables and can achieve analyses that are similar to, or more accurate than, the SC DA results [201]. Lee et al. (2016) [201] found that, compared to the SC DA approach, assimilating outlet streamflow using the WC DA approach resulted in a larger correlation between the a priori and updated states and produced similar or reduced RMSE of streamflow analysis and prediction. However, Maxwell et al. (2018) [142] reported that these mass constraints, more commonly applied to ensure that the non-negativity and capacity thresholds of model states were not exceeded, did little to improve forecast performance relative to the unconstrained and free run model outputs. In contrast, the combination of mass and flux constrained assimilation can improve the accuracy and reliability of streamflow predictions [142].

In general, a great number of studies have proved the potential of DA to effectively compensate for inaccurate estimations, substantially improving hydrological forecasting and explicitly dealing with various uncertainties (from model forcing data, model parameters, model structures, model initial and boundary conditions, etc.) (e.g., [21,28,108,125,179,191]). However, differences in the selected DA technique or its expansion, the hydrological model, the assimilated observation type, data availability, the specification and quantification of the model and observation errors, basin characteristics, and constrained or unconstrained DA would exert an effect on the performance of streamflow predictions [15,20,29,120,141,142]. Hence, the optimal selection of appropriate settings within a DA system based on catchment characteristics and data availability is crucial to provide less uncertain and more reliable forecast model outputs.

5. Summaries, Discussions, and Outlooks

In conclusion, the application of satellite-based remote sensing to improve streamflow predictions has received increasing attention. The popular observation variables mainly include precipitation, soil moisture, ET_a, SWE, SCA, TWSC, LST, and river width. Among them, SREs have been scarcely used within hydrological modeling, because they are generally inferior in driving hydrological models to ground observations. There are many reports about using satellite-based ET_a to enhance ET_a estimation itself, but few have aimed at improving streamflow simulations, because ET_a is not a state variable of hydrological models and is difficult to measure. For remotely sensed SWE and SCA, a number of studies have examined their utility in improving runoff estimations. Some findings have demonstrated improvements in both snow and streamflow predictions through using remotely-sensed snow observations. However, their limited contributions to, and even degradations in, the ability of streamflow simulations have been also reported. In terms of TWSC, relevant studies using GRACE-derived TWSC data to produce better streamflow estimation have been seldom mentioned. Moreover, in most cases, only modest or poor improvements have been obtained, mainly due to the low temporal and spatial resolutions of GRACE-derived TWSC data. The utility of LST and river width provided good to poor model performance. Furthermore, their applications seem to be more appropriate for large-scale catchments. Particularly, river width is unable to replace in situ observations, which is limited only to ungauged basins.

In contrast, more studies focused on applying remote sensing soil moisture products to improve simulated streamflow because of the important role of soil moisture in runoff generations. In early studies, satellite-based surface soil moisture was integrated into hydrological models, and, then, the root zone soil moisture was estimated and applied to the models to attain more accurate hydrological predictions. Moreover, several studies have employed the highest vertical error correlation in different soil layers for updating the subsurface soil moisture in surface runoff estimates. In addition, many studies have jointly used both soil moisture and streamflow (and/or snow data and TWSC data) to achieve better performance for hydrological forecasting. Meanwhile, new assimilation or calibration schemes have been developed, and different constraints to the data assimilation have been implemented to improve assimilation performance.

Overall, the aforementioned studies have made great contributions to hydrological modeling improvement through using satellite-based remote sensing. However, these results have shown more or less of a difference, owing to the differences in the selected hydrological model, catchment characteristics, assimilation or calibration procedures, and satellite-based observations. Thus, how to choose and apply remote sensing data to provide better streamflow estimates should be regarded cautiously, particularly in complex watersheds controlled by high-intensity human activities. For instance, in the Dagu River basin, located in the Shandong peninsula of China, river runoff has been almost zero, and some river reaches have dried up in the non-flood period over the past several decades [204]. Even in some dry years, the Dagu River might have been cut off over an entire year. This was mainly attributed to intense human activities, particularly water interception by cascade dams for human water consumption. Cascade dams separated the Dagu River into many similar long narrow lakes, which resulted in hydrological connectivity almost vanishing. Limited streamflow observations failed to provide sufficient information for judging the accuracy of hydrological modeling. Therefore, it will be a challenge to simulate hydrological processes in similar watersheds.

The application of satellite-based observations may help to achieve better model results. In light of this goal, a framework is recommended to help apply remotely sensed observations to improve hydrological modeling in highly regulated basins (the Dagu River basin, for instance). First, the information of land use/land cover (LULC) can be interpreted using high-spatial-resolution remote sensing data, such as Landsat images (30 m), Sentinel 2 (10 m), and GF-2 (1 m, 4 m). As one of the most important inputs into hydrological models, high precision LULC data can improve the simulation of the impact of human activity on hydrological cycles. Second, remotely-sensed soil moisture and ET_a can be jointly used in hydrological models, which were rarely reported in early studies. Better hydrological predictions can be achieved by comparing different simulation results from using remotely-sensed soil moisture, ET_a, or streamflow observations alone, as well as their respective combinations. Third, data assimilation and model calibration can be employed to extract useful information from remotely-sensed soil moisture and ET_a. Their contributions to hydrological estimations can be evaluated and compared to seek better model performance. In addition, ML approaches, such as ANNs and SVM, can be attempted to represent the complex and non-linear dynamics inherent to hydrological processes, complementary to hydrological models. Finally, the available data concerning cascade dams and water consumption can be added to hydrological models prior to parameter calibration or data assimilation to improve hydrological modeling. Generally, this framework may be a functional solution for hydrological modeling in human-dominated watersheds. In the future, it will be necessary to implement relevant studies to verify this framework's feasibility and effectiveness over highly regulated basins.

Encouragingly, the new development of remote sensing technologies, especially the new launch of satellites, has great potential to improve estimates of relevant hydrological variables for hydrological modeling, in terms of accuracy, resolution, and repeat times. For example, the Water Cycle Observation Mission (WCOM) will provide synergetic observations for key global water cycle parameters, which are focused on soil moisture, snow water equivalents, and freeze/thaw [205]. The second, third, and fourth spacecraft of the Joint Polar Satellite System (JPSS), JPSS-2, JPSS-3 and JPSS-4, will be launched in 2021, 2026, and 2031 respectively. These spacecraft will offer daily time series for retrievals of LST and ET, as well as vegetation parameters and snow cover products [55]. Several hyperspectral missions are planned, which can help to improve snow retrieval, vegetation monitoring, and ET estimates [55,206]. These upcoming missions would also benefit improvements of streamflow predictions, despite new, emerging challenges.

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