Integration of GRACE Data for Improvement of Hydrological Models

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1 Introduction

Observation is the first and most primary step in various disciplines of geosciences such as hydrology, meteorology, oceanography, geology, glaciology, and other planetary sciences. Hydrology or hydrological sciences which essentially deals with the question "What happens to the rain?" largely depends on gauge observations, which have been the longest running bastion furnishing long time series of datasets. Hydrological studies require datasets of both meteorological and hydrological variables such as temperature, humidity, precipitation, streamflow, etc. to monitor, understand, and model the complex physical processes which convert precipitation to surface water, soil moisture, groundwater, or streamflow. For a long time, hydrological studies were completely driven by datasets produced only by gauge measurements and to some extent field surveys. Although gauge measurements and field datasets are indispensable tools to understand the natural processes even today, they suffer from several limitations [6] such as

(i) localized nature of the gauges provides information only for a particular location;
(ii) gauges cannot provide data at locations inaccessible to humans;
(iii) data procured by gauges are not easily available due to political control over data sharing policies; and
(iv) management and maintenance of gauges are big challenges faced by concerned authorities.

Moreover, from hydrological modeling perspective, gauge datasets are quite limiting and do not help incorporate mathematical modeling of many physical processes. Consequently, development of a systematic framework that provides us with observational datasets of the Earth having the desired properties such as global coverage,

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continuously available in time, and accessible across political boundaries, specifically of hydrological and meteorological variables, was necessary. As a result, Earth-observing satellite remote sensing has been developed to complement the gauge-based observations and enhance our knowledge and understanding of various physical processes [52, 55, 57]. This has not only enhanced our ability to model complex hydrological processes [36, 53, 86] to a large extent but also improved our capabilities to predict and forecast hydrological extremes which have now reached new levels.

The journey of remote sensing observations started in 1972 with Earth Resources Technology Satellite (ERTS) 1 [14] launched by National Aeronautics and Space Administration (NASA), USA, which later came to be known as Landsat 1. It carried a multispectral scanner (MSS) recording data in four spectral bands, viz., red, green, and two infrared bands. Since then the technology used for remote sensing has grown by leaps and bounds. Remote sensing satellites now record not only in the optical and near-infrared bands but also in thermal and microwave bands. The spatial, spectral, temporal as well as radiometric resolutions have improved with each new satellite. New data acquisition techniques are being developed such as the synthetic-aperture radar (SAR) used to procure terrain and land cover information [44], satellite altimeters used to measure depth of seabed, radiometers used to estimate surface soil moisture [63], and hyperspectral imagers having a very high spectral resolution are used for various applications in the fields of agriculture, mineralogy, and environmental sciences [46].

The Terrestrial Water Storage (TWS) estimate derived from the Gravity Recovery and Climate Experiment (GRACE) satellite data is a remarkable addition to the vast set of remote sensing observations [76, 83]. Compared to the previous satellites, GRACE uses a completely different technique of data acquisition. While most of the previous satellites can observe only surface features of the land, GRACE satellites are able to acquire information about water storages in any form at any depth. TWS refers to the total water storage in a column of land present in the form, be it snow, ice, surface water, soil moisture, and groundwater. Although the spatial and temporal resolution of the GRACE data is coarse as compared to many other satellites, the unique nature of the data makes it an invaluable tool to observe terrestrial hydrological processes [79, 93]. The water storage that is the most difficult to observe and monitor is groundwater and *in situ* well observations were the only way to monitor them until the advent of GRACE. Well observations suffer from the obvious limitations of consistency, unavailability of data for the required period, inadequate spatial distribution of observation wells, and above all, political control over data for transboundary aquifers. GRACE on the other hand provides a global observational dataset periodically for the past 15 years. Using GRACE-derived datasets, scientists have identified depleting groundwater levels in different parts of the world such as Sacramento and San Joaquin River basins, California's Central Valley, and High Plains aquifer in USA [12, 23, 64, 65], Bengal Basin of Bangladesh [68] and Ganga–Brahmaputra–Meghna River basin [34] in South Asia, transboundary river basins in the Middle East [32, 88], Northern China [31] and Southern Murray Darling River basin [15] in Australia.

GRACE data is being used to solve a host of scientific problems other than the numerous studies related to groundwater. GRACE-derived TWS, also known as TWS Anomaly (TWSA) and its derivative TWS Change (TWSC), are used to study the dynamics of the terrestrial part of the hydrologic cycle and unravel its complex nature [5, 27, 45, 80]. It is used to understand water budget at the spatial scale of large river basins or continents [38, 79]. Terrestrial water budget, atmospheric water budget, or a coupling of the two is used to estimate evapotranspiration or river discharge [60, 59, 70, 79, 78]. Evapotranspiration is an important part of the terrestrial hydrological cycle as it is the terrestrial feedback to the atmosphere and affects the climate. However, it is a complex hydrological variable which is difficult to estimate by the various energy balance and aerodynamic methods as they are highly data intensive. GRACE provides a rather simple method of its estimation. River discharge is an equally important parameter affecting the seas and oceans, determining the freshwater input to the system. Ocean salinity, sea surface temperature, and various other parameters are dependent on the amount of freshwater that comes into the oceans in the form of river discharge. The GRACE-based method of river discharge estimation is specifically helpful for large rivers which do not have a defined stream but forms a large delta system as it meets the ocean, as in case of the rivers Ganga–Brahmaputra, Indus, Irrawaddy, Mekong, and Yangtze. GRACE also finds application in drought-related studies [29, 84]. Precipitation is typically used for drought identification, monitoring, and management. Recently, a few studies have also used soil moisture to monitor droughts. However, TWS data which is the total of all the water storages helps improve the impact assessment of a drought by providing a holistic estimate of the total amount of water lost during a drought and the time taken to regain.

The area of application of GRACE data which would be of interest for the present discussion is its integration into hydrological models, which are sophisticated tools used for prediction of various hydrological parameters. Prediction of river discharge has been the sole objective of hydrologic models for a long time due to the limited number of hydrological variables observed (as discussed earlier). However, with the increasing number of observations, specifically satellite-based observations and huge improvement in the computational capabilities, the structure and functions of hydrological models have also evolved. They now represent more complex processes at finer spatial and temporal scales and predict various hydrological parameters along with streamflow [17]. Integration of GRACE data into a hydrological model should further improve the representation of the physical processes and prediction of complex parameters such as evapotranspiration, soil moisture, and snow accumulation. In this chapter, we discuss in detail the various ways of integrating GRACE data into a hydrological model. We elaborate on the physics behind acquisition of TWS data through GRACE satellites and the available data products. We also review various hydrological models used for GRACE-based studies discussing models which are more often chosen over the others.

2 GRACE Data and Gravity Recovery

Before divulging into the details of integrating GRACE data with hydrological models, it is important to understand the science of gravity recovery. The GRACE satellite mission is a joint venture by the US and German space agencies, NASA and DLR (DeutschesZentrum furr̂ Luft-und Raumfahrt), respectively, under the NASA Earth System Science Pathfinder Program. The mission which was launched on March 17, 2002 consists of a pair of small and identical satellites (Fig. 1) orbiting at an altitude of 500 km from the Earth's surface with a separation between them of about 220 km along track. The satellites are connected by a highly accurate inter-satellite microwave K band ranging system constantly measuring the minute changes in the inter-satellite distance/range of the order of 10 μm. The distance between the two satellites changes due to the changes in earth surface features, which vary in density. Higher density relates to high mass, thus culminating into greater gravitational force and vice versa. If the Earth was homogenous in nature, the range between the two satellites would remain constant. However, the mass distribution is highly heterogeneous as well as constantly changing in time. The most dynamic constituent of the planet is water that circulates through the oceans, atmosphere, lithosphere, cryosphere, and biosphere. As a result, the time variable gravity signal acquired by the GRACE satellites through the measurement of the inter-satellite range rate mainly consists of the temporal variations of water as it moves from one storage compartment to another. After removing the fluctuations in the mass of the atmosphere and oceans, also known as Atmosphere and Ocean De-aliasing (AOD) from the total gravity signal, the seasonal and inter-annual fluctuations in TWS are obtained, expressed as centimeters of Equivalent Water Thickness (EWT) [73, 75, 76, 89].

The inter-satellite range rate, the primary variable observed by the GRACE satellites, must go through a long course of data processing to be converted to TWS. There are three primary centers constituting the Science Data System (SDS) which perform the processing of the Level 1 dataset to provide Level 2 and Level 3 datasets. These centers are the Center for Space Research (CSR) at the University of Texas at Austin, Jet Propulsion Laboratory (JPL), NASA and the German Research Center for Geosciences (GFZ) Helmholtz Center, Potsdam. The Level 1 data from GRACE consists of the inter-satellite range, range rate, range acceleration, and non-gravitational accelerations from each satellite. The Level 2 data product is the monthly gravity field estimates available in the form of spherical harmonic coefficients, whereas the Level 3 dataset is mass anomaly expressed in terms of EWT of TWS [39, 77]. The three data processing centers use different data processing techniques which include distinct static gravity models, different de-aliasing schemes and varied order and degree of the spherical harmonic coefficients to produce three separate datasets commonly known as CSR, JPL, and GFZ datasets. However, there are other research groups which also use other varieties of processing techniques to produce Level 2 and Level 3 data products such as the Delft Mass Transport (DMT) model of Delft University of Technology (TU Delft) [35, 43], ITG-Grace2010 of Bonn University, and a host of datasets produced by NASA's Goddard Space Flight Center (GSFC). JPL's TELLUS

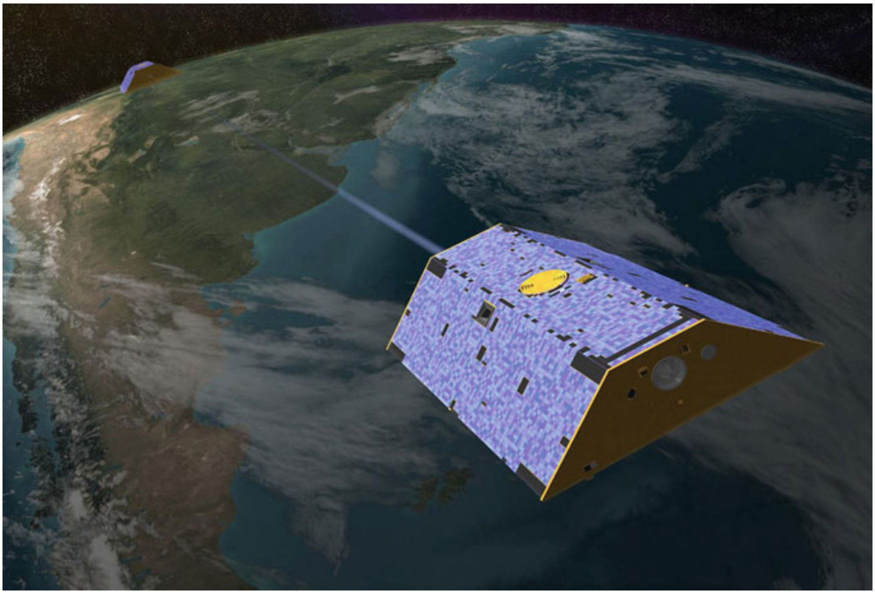

Fig. 1 Illustration of the twin satellites of the GRACE mission, connected by the along-track K-band microwave ranging system (Credits: NASA/JPL-Caltech)

website provides Level 3 monthly gridded as well as mascon products of GRACE TWS estimate derived from Level 2 dataset of the three primary data centers viz CSR, GFZ, and JPL. These products are easily accessible, available along with the error estimates and are ready to use for hydrologists [39].

3 Large-Scale Hydrological Models

Mathematical models of the hydrological processes, commonly known as hydrological models, have a long history as they evolved from simple lumped models with a single output to much more sophisticated stochastic distributed hydrological models which use several input variables and estimate wide range hydrologic responses [69]. Most of the primitive models are known as rainfall–runoff models which take rainfall and very primary land surface characteristics to estimate runoff. However, these models were an improvement over statistical models used for the prediction of runoff because the former contains representation of some physical processes and their usability in real time when forced with real-time precipitation [11]. With advancement in computational capabilities and proliferation of remotely sensed data, the hydrological models have hugely improved in terms of the simulation time steps, number of climatological forcings and land surface characteristics, spatial resolution, and number of output variables. These developments finally culminated to an increased number of physical processes represented within the models as well as the accuracy with which they are represented. Thus, the hydrological models of the new generation are of great use for prediction of various hydrologic variables such as runoff, streamflow, evapotranspiration, etc. which help for water resources management [8, 42, 71]. Moreover, they also provide a robust framework to run numerical experiments to understand the effects of various natural and anthropogenic changes in the land surface properties and climate such as deforestation, urbanization, expansion of agricultural land, global warming, increasing extreme rainfall, etc. [7, 24].

Another aspect of hydrological models that has changed with improvement in various technologies as well as the urge to improve the accuracy in prediction of large-scale hydrological processes is the expanse of the land surface modeled within a single framework. Most hydrological models refer to catchment or river basin scale modeling where the primary output variable of interest is the streamflow at the mouth of the river basin. However, these models are calibrated for a single catchment such that the model parameters are tuned to represent hydrologic and climatic processes occurring only within that catchment. A new variety of models are the Land Surface Models (LSMs) which are included within the atmospheric General Circulation Models (GCMs) to represent the interaction of the atmosphere with the land surface in the form of mass and energy exchange [10, 21].

As discussed earlier, the river discharges from the land surface into the oceans alter several of its physical properties which in turn affect the climate. As a result, these LSMs are coupled with a River Routing Model (RRM) to convert the runoff produced by the LSM to streamflow and finally the river discharge into the oceans. LSMs have evolved greatly over the past few decades to accurately represent the partitioning of the incoming net radiative energy into latent and sensible heat fluxes and the partitioning of precipitation into runoff, evaporation, and water storage. One such LSM is the Community Land Model (CLM), part of the Community Earth System Model (CESM) of the National Center for Atmospheric Research (NCAR), USA [10]. The hydrologic processes represented in the model (shown in Fig. 2) include interception of precipitation by canopy, throughfall, transpiration, soil evaporation, canopy evaporation, infiltration, runoff, soil moisture, aquifer recharge, snow accumulation, melt, and sublimation. Other than the hydrologic cycle, the model includes other physical processes such as land biogeophysics, biogeochemistry, ecosystem dynamics, and anthropogenic interventions (Fig. 2). A similar framework is the Noah-Multiparameterization Land Surface Model (Noah-MPLSM) which includes detailed vegetation dynamics including canopy shading and under-canopy snow dynamics along with the capability to differentiate between C3 and C4 pathways of photosynthesis [51, 92]. The Noah-MP LSM version 1.6 was implemented in Weather Research and Forecasting (WRF) Model version 3.6. WRF is a numerical weather prediction model developed mainly by NCAR and National Centers for Environmental Prediction (NCEP).

LSMs coupled within a GCM framework are not the only large-scale hydrological models simulating the water and energy cycles along with geochemical processes and vegetation dynamics. There are many large-scale uncoupled or stand-alone LSMs, sometimes also known as the Global Hydrological Models (GHMs) simulating phys-

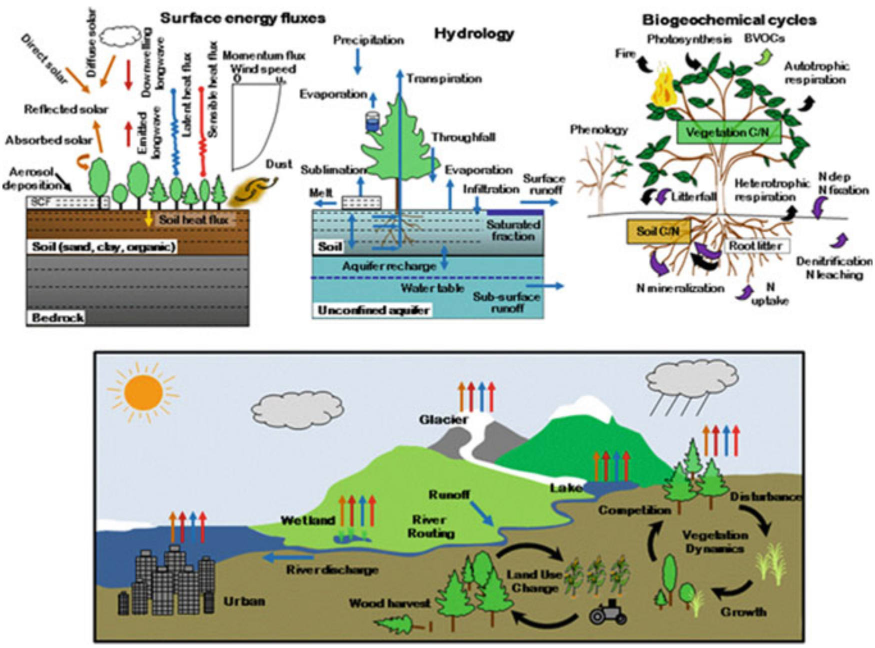

Fig. 2 A schematic diagram showing the energy cycle, hydrological cycle, biogeochemical, vegetation dynamics, and land use change represented within the Community Land Model (CLM) (Credits: http://www.cesm.ucar.edu/models/clm/)

ical processes at global scale such as the WaterGAP model (Water—Global Analysis and Prognosis model) [2], developed by University of Kassel and University of Frankfurt, Germany, PCR-GLOBWB (PCRaster GLOBal Water Balance model) [96] conceived by Utrecht University, The Netherland, ISBA-TRIP (Interactions between Soil, Biosphere, Atmosphere—Total Runoff Integrating Pathways) [3, 19] created by Centre National de Recherchés Météorologiques, France and the Global Land Data Assimilation System (GLDAS) framework [61], developed by GSFC and NCEP. The WaterGAP model is designed for the assessment of macro-scale processes of the terrestrial hydrological cycle, taking into consideration anthropogenic component to simulate freshwater availability and irrigation water use. PCR-GLOBWB includes subgrid schemes for partitioning of rainfall into runoff, infiltration, interflow, groundwater recharge, and baseflow, as well as routing of the generated runoff. The model includes detailed anthropogenic effects to the extent that it includes more than 6000 manmade reservoirs. Thus, the human water use is completely integrated into the hydrological model at time step, calculating water demand, surface and groundwater abstraction, consumptive water use, and return flow. ISBA is a relatively simple LSM calculating variability in energy and water budgets with a saturation excess overland flow approach to simulate runoff based on TOPMODEL hydrological model [9]. This is coupled with TRIP, a simple RRM which converts runoff simulated by ISBA into river discharge for a global river network. The GLDAS framework consists of four different LSMs, viz., Mosaic, CLM, Noah, and Variable Infiltration Capacity (VIC) models forced by a single forcing dataset. These four models differ mainly in the depth of soil considered for the simulation of soil water interaction and storage as well as the number of layers into which the total depth is divided. It should be noted that both the ISBA-TRIP model and the GLDAS set of models do not include any anthropogenic effects of water storage and water use. Although the LSMs are of great use, a major challenge lies in the calibration of these models which can only be carried out using vegetation indices or streamflow for large river basins by routing the simulated runoff. GRACE provides a very useful data first for the evaluation of such LSMs and eventually can be assimilated into the models for better estimation of various hydrologic variables. In the following sections, these two approaches of integration of GRACE data are discussed in detail.

4 Evaluation of Model Simulations Using GRACE Data

As discussed in the previous section, coupled and uncoupled LSMs try to simulate several hydrological variables by incorporating most complex of the physical processes, mimicking them to the maximum extent possible. Scientists are continuously trying to improve these models by better parameterization and adding more and more hydrological, geophysical, and biophysical processes into these models. A handy dataset for quick evaluation of the hydrological fields simulated by these models is the GRACE dataset. Due to its continuous global coverage, GRACE data could be used for evaluation of LSMs in cold regions affected by snow, arid, and semi-arid regions characterized by very low or no soil moisture conditions as well as areas characterized by a heavy to very heavy monsoonal rainfall. Table 1 provides a detailed chronological list of various studies carried out at global, continental, regional, and river basin scales to compare and evaluate various LSMs to estimate the accuracy with which it simulates various water storages and physical processes affecting them. Some studies tried to improve the estimation of certain variables by incorporating better and more detailed process representation and validated the improvements by comparison with GRACE data. The CLM LSM of NCAR is one such model which has seen continual efforts of betterment and corresponding evaluation using GRACE data. One of the limitations observed with CLM 2.0 was its representation of frozen soil which included completely frozen soil in areas with temperature below 0 °C, resulting in higher and earlier than expected runoff caused by spring season rainfall. The modifications suggested were allowance for the coexistence of ice and water in soil, the concept of a fractional permeable area, and considering both liquid water and ice together as soil moisture for calculating hydraulic conductivity. These modifications improved both the surface runoff and the soil water storage estimates of CLM when the simulations were evaluated for river basins in the cold regions, viz., Lena, Yenisei, Mackenzie, Ob, Churchill-Nelson, and Amur using both streamflow and GRACE data [48, 49]. Another deficiency of the CLM model was its inability to model the groundwater dynamics as the column of soil considered extends only to 3.8 m below the surface. In another attempt to improve the CLM model, a Simple Groundwater Model (SIMGM) which represents an unconfined aquifer along with the recharge and discharge processes was included within the framework [50]. Although the modification worked out well for all the 12 river basins considered in the study, it is not expected to do well in cold regions where the water table is exposed to freezing conditions due to the obvious differences in the physical processes. In a more recent attempt to accurately represent groundwater dynamics within the CLM model version 4.5, it was found that addition of a no-flux boundary condition at the base of the soil layer improved the estimate. As a result, these simulations from the improved CLM models were found to agree well with GRACE-derived TWS observations [72].

A few studies also tried to improve the ISBA-TRIP hydrological model by comparing modified versions of the model with GRACE data. Initial comparisons of the model with GRACE data outlined some model deficiencies such as the high storage in the form of surface water within the river channel as a part of the routing scheme overestimated the maximum and underestimated the minimum TWS values mainly in the tropical region. Other deficiencies within the ISBA-TRIP model were the calculation of evaporation and snow accumulation. However, the major limitation was identified as the oversimplified routing model and the absence of anthropogenic effects within the model [3, 19, 54, 87]. Although human impact was not included in the modified version, improvements were suggested for TRIP—the routing model which included a simple groundwater reservoir and a variable streamflow velocity calculation. Several other LSMs were evaluated globally or regionally using GRACE data. Inclusion of a water exchange scheme between continents and oceans included in the Organising Carbon and Hydrology in Dynamic Ecosystems (ORCHIDEE) LSM resulted in better simulation of land water storage [Ngo-Duc et al., 2007]. GRACE data when compared to the Australian Water Resource Assessment (AWRA) model suggested a need for improvement in representations of diffuse groundwater discharge processes and interaction between surface and groundwater [van Dijk et al., 2011]. Doll et al. [2014] found that the WaterGAP model version 2.2 underestimates TWS as compared to GRACE with a phase lag of a month observed between the two. Evaluation of the GLDAS framework-versions 1 & 2 carried out for China by Wang et al. [2016] showed inconsistency in the rate of change of TWS. The four land surface models (Noah, SAC-Sacramento Soil Moisture Accounting Model, (VIC) Variable Infiltration Capacity Model, and Mosaic) applied in the newly implemented National Centers for Environmental Prediction (NCEP) operational and research versions of the North American Land Data Assimilation System version 2 (NLDAS-2) were also evaluated using GRACE data [Xia et al., 2016]. A common source of inconsistency ob-served between the GRACE observation and model simulation was attributed to the error and uncertainty present in the precipitation dataset which is a primary forcing for all hydrologic models.

Table 1 Comparative list of studies evaluating and comparing hydrological models with GRACE data

Authors (Year)	GRACE data	Model	Input data	Study region	Study period
Niu and Yang [49]	Chen et al. [16], Seo and Wilson [67]	CLM 2.0 with SIMTOP	GLDAS 1-degree 3-hourly data (2002–2004)	Lena, Yenisei, Mackenzie, Ob, Churchill-Nelson and Amur	August 2002–July 2004
Niu and Yang [48]	Chen et al. [16], Seo and Wilson [67]	CLM and Modified CLM	GLDAS 1-degree 3-hourly data (2002–2004)	Global and Ob, Yangtze, Amazon, Taz and Ural River Basin	August 2002–July 2004
Swenson and Wahr [74]	Swenson and Wahr [73]	Atmospheric and Terrestrial Water Balance model	GCM output and NCEP/DOE R-2 for atmospheric water balance and GLDAS/Noah LSM for terrestrial water budget	Mississippi and Ohio-Tennessee River basins	June 2002–April 2004
Ngo-Duc et al. [47]	Ramillien et al. [56]	ORCHIDEE modified to include a routing scheme	P: 6-hourly NCEP/NCAR constrained by monthly CMAP; Others: 6-hourly NCC (NCEP/NCAR) corrected by CRU atmospheric forcing	Global and Amazon, Congo, Niger, Mississippi, Yangtze, Ganges, Brahmaputra, Mekong	May 2002–December 2003
Niu et al. [50]	Chen et al. [16], Seo and Wilson [67]	Modified CLM with SIMTOP and SIMGM	1-degree 3-hourly GLDAS dataset (2002–2004)	12 Global river basins not affected by snow or ice	August 2002–December 2004
Alkama et al. [3]	CSR-RL04, JPL-RL 4.1, GFZ-RL04 estimates	ISBA-TRIP	3-hourly 1-degree Princeton University data	Global and 33 large river basins	Aug 2002–Dec 2006
Decharme et al. [19]	CSR-RL04, JPL-RL4.1, GFZ-RL04 estimates	TRIP with groundwater storage and variable flow velocity	Runoff simulated by ISBA of Alkama et al. [3]	Global and 12 large river basins	Aug 2002–Dec 2006
van Dijk et al. [97]	1-degree gridded TWS estimates from CSR	Australian Water Resource Assessment (AWRA)	0.05-degree gridded meteorological forcings obtained by interpolation of Station data	Continental Australia	January 2003–December 2010
Grippa et al. [27]	RL04 of CSR, JPL and GFZ, DEOSDMT, GRGS-EIGEN-GL04 and 10 day, 4° GSFC	HTESSEL, ORCHIDEE-CWRR, ISBA, JULES, SETHYS, NOAH, CLSM, SSiB, SWAP	Rainfall: TRMM 3B42, Atmospheric forcings: ECMWF short-term forecast data Downwell Radiative fluxes: mix of ECMWF and Land Surface Analysis Satellite Applications Facility	West Africa	Jan 2003–Dec 2007

(continued)

Table 1 (continued)

Authors (Year)	GRACE data	Model	Input data	Study region	Study period
Pedinotti et al. [54]	CSR-RL04, JPL-RL4.1, GFZ-RL04 estimates	ISBA-TRIP	TRMM-3B42 and RFE-Hybrid rainfall for ISBA-TRIP CHS, other atmospheric forcings from ECMWF	Niger River Basin	Jan 2003–Dec 2007
Vergnes and Decharme [87]	CSR-RL04, JPL-RL 4.1, GFZ-RL04 estimates	TRIP	Total runoff from ISBA simulation by Alkama et al. [4]	Global and 12 large river basins	August 2002–August 2008
Rosenberg et al. [62]	I-degree gridded CSR dataset	VIC modified to include SIMGM	1/8th-degree Gridded from precipitation and maximum/minimum temperature data from NOAA Cooperative Observer stations and wind data from NCEP-NCAR reanalysis	Colorado River Basin	2002–2010
Cai et al. [13]	1-degree gridded TWS estimates from CSR RL4.0	Noah-MP	NLDAS Phase 2 atmospheric forcing at 1/8° resolution	Mississippi River Basin	2003–2009
Doll et al. [20]	0.5-degree gridded GFZ-RL05, CSR-RL05 and ITG-Grace2010	WaterGAP 2.2	Daily climate dataset WFD (WATCH Forcing Data)/WFDEI (Watch Forcing Data ERA-Interim)	Global	2003–2009
Swenson and Lawrence [72]	CSR RL05	CLM version 4.5 with modification	1.25 longitude × 0.9 latitude ECMWF ERA-Interim Reanalysis data	Lower Colorado River basin, in the southwestern United States, and a region in northeastern Australia	2002–2014
Ahmed et al. [1]	1-degree gridded TWS estimates from CSR RL05	CLM4.5-SP and GLDAS-Noah	GLDAS: NOAA and CPC/CMAP and CLM: CRU/CRUNCEP	Continental Africa (Niger, Zambezi, Okavanko, Limpopo)	2003–2010
Wang et al. [90]	GRACE Tellus RL05 CSR, JPL, GFZ	GLDAS1 (Noah, CLM, Mosaic, VIC) GLDAS2 (Noah 3.3)	ECMWF & NCEP–NCAR reanalyses data, NOAA/GDAS and Princeton University atmospheric fields, AGRMET radiation fields,	China	2002–2010

(continued)

Table 1 (continued)

Authors (Year)	GRACE data	Model	Input data	Study region	Study period
Xia et al. [91]	GRACE Tellus RL05 CSR, JPL, GFZ average	NLDAS-2 operation (Mosaic and Noah) and research (SAC-Clim and VIC4.0.5)	CPC, PRISM & NARR precipitation data and 2-m air temperature from NARR	USA	2003–2014
Zhang et al. [95]	GRACE RL05 Level-2 products from GFZ	LSDM, WGHM, JSBACH, MPI-HM	WFDEI dataset based on ERA-Interim reanalysis data	31 largest river basins	2003–2012

5 GRACE Data Assimilation

Data assimilation is a statistical technique of combining the simulations or forecasts from a prediction model with measurements from an observing system to produce improved estimates. Evaluation of LSMs has been one of the most explored techniques of utilizing GRACE data for the improvement of model physics and simulation accuracies. However, it is an indirect method where model deficiencies are figured out by comparing model outputs with GRACE observations followed by improving model physics solely based on our understanding of the intricate details of hydrological processes. This to some extent is limiting since the knowledge and understanding of the hydrological processes are itself limited and the large information hidden within the GRACE observations may be completely overlooked. As an alternate method of data integration, GRACE data assimilation techniques were explored where the observational dataset is directly utilized to improve the model simulation at each time step. Although it apparently does not improve model physics or our understanding of hydrological processes, GRACE data assimilation improves model simulations to a great extent, also facilitating spatial and temporal disaggregation of GRACE data as a byproduct. Table 2 gives a detailed chronological list of studies performed in this field of research.

The assimilation of GRACE data into LSMs has two major challenges. The typical temporal and spatial resolution of the GRACE observation is much coarse as compared to the LSMs. The GRACE data provided by NASA JPL's TELLUS website has a spatial resolution of ~100 km (1 degree) and a temporal resolution of a month. On the contrary, most LSMs are run at a daily or sub-daily scale, with the spatial resolution varying from 5 km (0.05°) to a maximum of 50 km (0.5°). Hence, the process of data assimilation invariably includes a spatial and temporal disaggregation technique. Consequently, a widely used and efficient data assimilation technique, known as the Ensemble Kalman Filter (EnKF) [22], is used in most of the previous literature (Table 2). The EnKF is a variant of a statistical technique known as the Kalman filter and is used for large problems. It has the inherent assumptions that the probability

Table 2 Comparative list of GRACE data assimilation studies

Authors (Year)	GRACE data	Model	Input data	Study region	Study period	Assimilation method
Zaitchik et al. [94]	CSR (RL01), GFZ (RL03), JPL (RL02)	CLSM	GLDAS forcing database	Mississippi (4 sub-catchments)	January 2003–May 2006	Ensemble Kalman Smoother
Houborg et al. [29]	CSR-RL04	CLSM	NLDAS-2 ad GLDAS data for study period model run and Princeton University data for long-term simulation	North America	August 2002–July 2009	Ensemble Kalman Smoother
Li et al. [41]	CSR-RL04	CLSM	GLDAS forcing database	Western and Central Europe	August 2002–July 2009	Ensemble Kalman Smoother
Huang et al. [30]	CSR-RL05	Noah-MP	0.1-degree, 3-hourly, near-surface meteorological dataset produced by the ITPCAS	Yangtze River basin	Jan 2003–Dec 2010	Proposed framework
Reager et al. [58]	CSR-RL05	CLSM	Same as Zaitchik et al. [94]	Mississippi river basin	April 2002—Dec 2014	Ensemble Kalman Smoother
Tangdamrongsub et al. [82]	CSR-RL05	OpenStreams wflow_hbv model (HBV-96)	European Climate Assessment & Dataset (ECA & D), ENSEMBLES project and Princeton University Dataset	Rhine river basin	Dec 2003—Oct 2007	Ensemble Kalman Filter
Girotto et al. [25]	Gridded CSR-RL05	CLSM	MERRA	USA	Jan 2003—Dec 2013	Sequential Kalman filtering technique

(continued)

Table 2 (continued)

Authors (Year)	GRACE data	Model	Input data	Study region	Study period	Assimilation method
Schumacher et al. [66]	TWS values using WGHM, ITG-GRACE2010 error covariance	WGHM	CRU TS 3.2, GPCC, WFDEI	Mississippi river basin	August 2003	EnKF, SQRA, SEIK
Girotto et al. [26]	Gridded CSR-RL05	CLSM	MERRA	India	Jan 2003–Aug 2015	3D Ensemble Kalman Filter
Khaki et al. [33]	ITSG-Grace2014	W3RA	Princeton University forcing dataset	Australia	Feb 2002–Dec 2012	(stochastic) EnKF, ETKF, SQRA, DEnKF, EnSRF, EnOI and PF with Multinomial (PFMR) and Systematic (PFSR) Resampling
Tangdamrongsub et al. [81]	CSR-RL05	PCR-GLOBWB	ECMWF Era-Interim, TRMM, CRU, Princeton and China Daily Ground Climate Dataset	Hexi corridor in Northern China	April 2002–Dec 2010	EnKF with and without errors
Tian et al. [85]	JPL-RL05 M, 3-degree mascon product	W3 Model	WFDEI forcing data, Global Tree cover fraction map and MODIS white-sky albedo	Australia	Jan 2010–Dec 2013	EnKF and EnKS

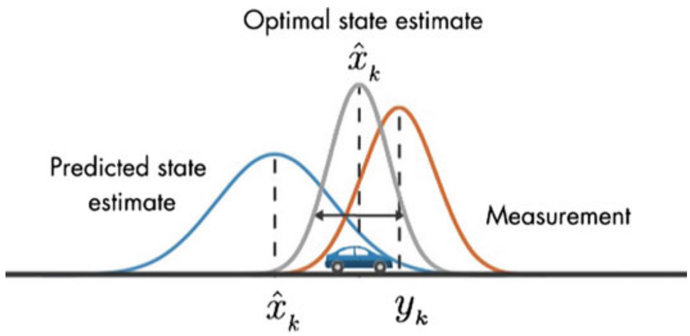

Fig. 3 A schematic diagram showing the concept of a typical Kalman Filter (Credit: Melda Ulusoy, MathWorks)

distributions are all Gaussian and the predictive model is linear. The Kalman filter (Fig. 3) is a recursive filtering mechanism which combines the simulation of a model and a noisy measurement, both of which are assumed to be Gaussian distributions to estimate the most likely state variables. The model estimate is generally less probable and contains more uncertainty than the measurement. However, the use of the EnKF provides an optimal estimate of the state variable which is much more probable and contains less uncertainty as compared to both the model prediction and the measurement, as shown in Fig. 3.

The second challenge is the hydrological variable of interest. GRACE observations result into TWS data which, as discussed earlier, is the aggregation of all the surface and subsurface water storages. To assimilate GRACE TWS data, there needs to be a hydrological variable within the model to which it can be mapped. The problem in this case is that all hydrological models have separate surface and subsurface storages modeled as different processes. Even if all the storages are added up to create a hydrological variable to be mapped against GRACE TWS data, it falls short due to the absence of groundwater storage. Most of the hydrological models incorporate groundwater dynamics as a boundary condition at the bottom of the soil column considered which is typically 2–4 m in depth from the ground surface. To resolve this issue, the catchment land surface model is the most preferred LSM used for assimilation as it contains an unconfined groundwater reservoir. Several studies have assimilated the GRACE TWS data with one of the primary objectives being improvement of groundwater estimation. Zaitchik et al. [2008] assimilated GRACE data into the CLSM using an ensemble Kalman smoother. Results indicated an improved correlation between observed ground-water and data assimilated simulated groundwater. In a similar effort, GRACE data was assimilated into the OpenStreams wflow_hbv model using an ensemble Kalman filter for the Rhine river basins. Results show increase in correlation between observed and simulated groundwater from 0.6 to 0.7 and 15% reduction in RMSE as a result of this data assimilation [Tangdamrongsub et al., 2015]. In both the cases, slight improvement in streamflow simulation was also observed. Tangdamrongsub et al. [2017] showed that assimilation of GRACE data increased the accuracy of groundwater estimate, simulated for a semi-arid region in northern China by PCR-GLOBWB by 25%. GRACE data assimilation was also carried out with the objective of drought assessment because most frameworks lack information of groundwater and soil moisture of deeper layers. Houborg et al. [2012] and Li and Rodell [2015] assimilated GRACE data into CLSM model to derive drought indicators for North America and conterminous US respectively. A similar exercise was carried out for western and central Europe by Li et al. [2012]. These efforts disaggregated GRACE data in both spatial and temporal dimension. GRACE data assimilation was also carried out to estimate human induced changes in TWS and assess regional flood potential [Y Huang et al., 2015a; Reager et al., 2015]. Further studies concentrated on improving the data assimilation using better variants of the ensemble Kalman Filter and other hydrologic dataset such as the soil moisture from Soil Moisture and Ocean Salinity (SMOS) mission [Girotto et al., 2016; Girotto et al., 2017; Khaki et al., 2017; Schumacher et al., 2016; Tian et al., 2017].

6 Conclusions

The hydrological models altogether have improved from the simple lumped models and now include not only hydrological processes but all such physical, chemical, and biological processes that affect or is affected by water (a typical example of which is shown in Fig. 2). Integration of GRACE data into hydrological models has improved their model physics and prediction capabilities. Such models now represent better dynamics of frozen soil, dry soil in arid climate, groundwater, and vegetation. This also improved the estimation of various hydrological and vegetation parameters. Further improvements were achieved by GRACE data assimilation into hydrological models with the added advantage of disaggregation of GRACE TWS observations. Moreover, the GRACE data processing techniques have also improved with the most recent studies using Release 05 dataset which has a much higher accuracy as compared to the initial releases. The GRACE Follow-On (GRACE-FO) mission is scheduled to be launched in 2018 which is expected not only to continue the unique GRACE observations but also to have some improvements as compared to its forerunner [18]. Meanwhile, scientists are still working on the processing techniques of the GRACE data and the new Release 06 of the GRACE dataset having better accuracy is available for use [28]. Thus, there are numerous avenues in which further improvement is possible that will unravel new vistas of knowledge in future.

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