Recent advance in earth observation big data for hydrology

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ABSTRACT
In the past three decades, breakthroughs in satellites and remote sensing have highly demonstrated their potential to characterize and model the various components of the hydrological cycle. A wealth of satellite missions are launched and some of the missions are specifically designed for hydrological research. Given the massive big data for hydrology, it is time for hydrology to embrace the fourth paradigm, data intensive science. This paper aims to highlight available and emergent technologies and missions in the field of Earth observation that have contributed greatly to hydrological science, the current status of those technologies and their improvements in our understanding of hydrological components, and to identify the important and emerging issues in Earth observation data applications in hydrology. This review will provide the readers with detail of Earth observation progress applications in hydrology.

1. Introduction

Over the past few decades, leaps in sensor technology has brought unprecedented advances in Earth observation (EO). New satellite, airborne and ground-based remote sensing systems are springing up all over the world (Butler, 2014; Ramapriyan & Murphy, 2017). These tremendous achievements have led to an explosion of Earth observation data, from low to high spatial, temporal and radiometric resolution, increasing at a breathless pace, both in size and variety (Guo, Wang, Chen, & Liang, 2014). For example, within the time you read the above sentence, NASA could have collected 1.73 gigabytes of data from around 100 missions which are active currently1. During the year ending in September 2016, the Earth Data Search Capability (EDSC) of NASA's Earth Science Data Systems (ESDS) distributed over 1.5 billion files of data (over 14.6 petabytes) to users all over the world (Ramapriyan & Murphy, 2017). It goes without saying a new era have been boosted in the field of Earth observation, a big data era (Bargellini et al., 2013; Nativi et al., 2015).

Hydrology, or hydrologic science is the “science of water” in nature, which is defined by National Research Council (NRC) as a distinct geoscience “a geoscience interactive on a wide range of space and time scales with the ocean, atmospheric, and solid earth sciences as well as with plant and animal sciences” (National Research Council, 2012). Water is critical to

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sustaining life on Earth as all living organisms require water. The circulation of water flux from atmosphere to land surface or ocean plays a critical role in shaping the surface of Earth, creating vegetation pattern, and driving the atmosphere processes. However, the currently ongoing rapid global change (i.e. land use and climate change) tremendously alters our environment and has significant altered hydrological processes, causing a great variety of water issues, such as water scarcity, drought, flood, water pollution, and therefore forms a serious threat to society development, slowing economic growth, threatening community health so on and so forth (ICWE, 1992). Understanding the causes and of changing hydrology is necessary for water management and policy. Such situations have highlighted the need of hydrology and brought spurt of interest in water cycle in the recent years. Due to the inherent and pervasive irregularity of Earth’s surface and subsurface properties, hydrological processes are one of the complicate phenomes with high variability over a broad range of spatial and temporal scales, making it challenging to characterize hydrological component and processes.

In the past three decades, breakthroughs in satellites and remote sensing have highly demonstrated their potential to characterize and model the various components of the hydrological cycle (Engman & Gurney, 1991; McCabe et al., 2017; Tang, Gao, Lu, & Lettenmaier, 2009). This has become a fast-growing field in hydrology. A wealth of satellite missions are launched, offering the data-sets covering every geoscience sphere, including land surface, energy, climate elements, water vapor, so on and so forth. Some observation systems are specifically designed for hydrological research. For example, new remote sensing missions like Soil Moisture and Ocean Salinity Mission (SMOS) (Kerr et al., 2010), Global Precipitation Measurement (GPM), Soil Moisture Active and Passive (SMAP), Gravity Recovery and Climate Experiment (GRACE) are producing valuable information to improve our understanding of water cycle. The emerging satellite missions have provided massive data for hydrology. For example, NASA SMAP send back 458 GB data for soil moisture every day. It is time for hydrology to embrace the fourth paradigm, data intensive science (Peters-Lidard et al., 2017).

Our focus within this paper is to highlight these available and emergent technologies and missions in the field of EO that have contributed greatly to hydrological science, the current status of those technologies and their improvements in our understanding of hydrological components, and to identify the important and emerging issues in Earth observation data applications in hydrology. This review will provide the readers with detail of Earth observation progress in hydrology.

2. Motivation for use of remote sensing in hydrology

2.1. Difficulty in hydrological cycle and components characterization

Hydrological cycle is an extremely complicated dynamic phenomenon as it occurs through a wide range of Earth processes associated with atmosphere, land, oceans, and the life on the Earth (Figure 1). Water cycle varies significantly across multiple spatiotemporal scales, with the time scale ranging from seconds to decades and longer, and the spatial scale from millimeters to planetary. It interconnects the water, energy, and biogeochemical cycles. For example, the circulation of water from atmosphere to land surface or ocean is highly coupled
with the exchange of energy. Under such circumstance, the impacts of climate change or human activities on one aspect of the water cycle are consequently transferred to other components or processes. Hence, understanding water cycle dynamics in a changing environment requires detailed information about the spatial and temporal characteristics of key hydrological flux, climate drivers or human activities, etc.

Traditionally, hydrological flux is measured by in situ monitoring systems. Though ground-based measurements are essential for hydrological science in the early stage, they are subject to the limitations including sparse spatial coverage of the existing stations, temporal gaps and delays, inconsistencies among measurements, unwilling to share of many governments, cost extremely high. It is inadequate to capture the spatial and temporal variation of hydrological flux. Remote sensing provides a good opportunity for hydrological flux, such as precipitation, soil moisture, water storage, as well as climate and environmental conditions, such as temperature, vegetation, carbon flux.

2.2. The emerging global hydrology

Eagleson (1986) first claimed the emergence of global-scale hydrology in 1986. He declared hydrological cycle is a global phenomenon and the human impact on hydrology surpass the scale of an individual catchment to a global dimension (Bierkens, 2015). The concept of global hydrology has become much more widely accepted by the mid-1990s, as human are changing the environment such as land use at continental scale and those changes have had significant impact on water balance, surface energy, and climate both at regional and global scale. It is recognized that both natural- and human-induced climate variations...
manifest themselves in the global water cycle, which leads to a growing awareness of addressing the water issues on global scale (Bierkens, 2015; Bierkens et al., 2014; Jones, 2014). A wide variety of data on global scale are required to better understand climate change as well as human impact on hydrology on global scale. At that time Peter Eagleson promoted global hydrology, it was kind of impossible to conduct such research due to the data limitation on the global scale. However, situation has changed 30 years later. A wealth of remote-sensing-based global data-sets are available for global hydrological processes modeling and prediction, which has flourished research field of global hydrology.

3. Earth observation missions relevant to hydrology

There are hundreds of sources of satellite monitoring systems, offering a diverse range of data-sets describing land surface, energy, climate elements, water vapor, so on and so forth. Some observation systems are specifically designed for hydrological research. Among the present 19 National Aeronautics and Space Administration (NASA) Earth science missions, 8 of those missions are highly relevant to hydrology, such as the SMAP, GPM, GRACE (Figure 2). NASA is going to launch some hydrology-related missions in the near future, including Ice, Cloud, and land Elevation Satellite-2 (ICESat-2) (to be launched in 2018) and Surface Water & Ocean Topography (SWOT) mission (to be launched in 2020). The European Space Agency (ESA) has eleven missions in orbit, four of them are relevant to hydrology, named CryoSat-2, EUMETSAT satellites, SMOS and Sentinel-1. ESA is planning to launch Earth Cloud Aerosol and Radiation Explorer (EarthCARE) satellite mission, which will advance our

![Figure 2. Earth observations of NASA (from NASA).](image)
understanding of the role that clouds and aerosols in reflecting solar radiation. Meanwhile, China have seen a spurt development in Earth observation over the past three decades. One hundred and ninety two Earth observation missions are in orbit,² with several missions related to hydrology, like Fengyun serial satellites, Haiyang serial satellites. China is going to launch Water Cycle Observation Mission (WCOM), which will directly focus on water cycle to provide integrated, high accuracy and consistent measurement hydrological flux (Shi et al., 2016). The major ongoing and future missions highly relevant to hydrological cycle are summarized in Table 1.

Apart from the Earth observation missions, a number of national and international activities and initiatives focused on joint advancement of Earth observation and hydrologic science have been directed. These activities include the International Precipitation Working Group (IPWG), the NASA Energy and Water Cycle Study (NEWS, http://nasa-news.org), European Union WATer and global Change (WATCH, http://www.eu-watch.org), the Global Energy and Water-cycle Experiment (GEWEX) LandFlux initiative (https://www.gewex.org/), and so on. NASA NEWS is established in 2003, which aims to use the global Earth observation and climate models to quantify the hydrologic consequences of climate change and produce useful seasonal and longer-range hydrologic predictions. To achieve the goal, NASA has collaborated with other agencies, like National Oceanic and Atmospheric Administration (NOAA), National Science Foundation (NSF), US Geological Survey (USGS). IPWG, found in 2000, is an international working group which brings together scientific community to exploit global precipitation estimation. IPWG has been in cooperation with Global Precipitation Climatology Project (GPCP, Adler et al., 2003).

With those efforts of Earth observation missions and activities, hydrology has inevitably entered an era of “Big Data” which will open a new vision for the advancement of hydrology (Peters-Lidard et al., 2017).

3.1. Precipitation

Precipitation plays a dominant role in water cycle, acting as the source of water for all livings and drives the other water cycle processes (Bunde, Büntgen, Ludescher, Luterbacher, & von Storch, 2013; Wu, Christidis, & Stott, 2013). Continuous and accurate estimation of global precipitation is essential to understand and predict the water flux movement and earth

| Hydrological cycle component | Mission/sensor | Standard spatial resolution | Standard temporal resolution | Launch year |
|-----------------------------|----------------|----------------------------|-----------------------------|-------------|
| Precipitation               | GPM            | 5 km                       | 0.125 days                  | 2014        |
| Evapotranspiration          | Terra/MODIS    | 0.5 km                     | 1 days                      | 1999        |
|                            | Aqua/MODIS     |                            |                             | 2002        |
|                            | Landsat 8      |                            |                             | 2013        |
|                            | Landsat 9      |                            |                             | 2023        |
| Snow and ICE cover          | ICESat-2       | 0.01                       | 33 days                     | 2018        |
|                            | CryoSat-2      | 0.25                       | 369 days                    | 2010        |
| Evapotranspiration          | Terra/MODIS    | 0.5                        | 1 days                      | 1999        |
| Soil moisture               | SMOS           | 36                         | 3 days                      | 2011        |
|                            | SMaP           | 36                         | 3 days                      | 2015        |
| Streamflow                  | SWOT           | 0.1                        | 11 days                     | 2021        |
| Groundwater                 | GRACE          | 220                        | 30 days                     | 2002        |
| Water cycle                 | WCOM           | 2–5                        |                             | 2020        |
surface energy cycles, such as flood, long-term water supply trends and storm prediction. Unlike the acquisition of more homogenous meteorological elements such as temperature, the stochastic and rapidly evolving nature of precipitation makes it extremely challenging to obtain high-quality precipitation measurement (Min, Zhang, Zwiers, & Hegerl, 2011). Traditional ground-based global precipitation observations are so limited because of the sparse station density especially in ocean and remote areas, while the radar observations are insufficient because of the “target homogeneity” problem.

Satellite-based remote sensing has been an important alternative for precipitation measurement and is the only way to measure global precipitation (Bitew & Gebremichael, 2011; Ebert, Janowiak, & Kidd, 2007; Kidd et al., 2012; Tian & Peters-Lidard, 2010). For satellite-based precipitation estimation, three kinds of radiation can be used, including visible (VIS), infrared (IR), and microwave (MV). In the early stage, Geostationary Earth Orbital (GEO) satellites, such as National Oceanic and Atmospheric Administration (NOAA) Geostationary Operational Environmental Satellite (GOES) provides observations with high frequency, at every 15–30 min. Instead of measuring precipitation directly, this kind of observation infers precipitation by obtaining the cloud top temperatures through VIS and IR images (Bellerby, 2004; Tang et al., 2009; Thies, Nauß, & Bendix, 2008; Yan & Yang, 2007). Microwave techniques are then applied into rain monitoring, such as Tropical Rainfall Measuring Mission (TRMM), Advanced Microwave Scanning Radiometer-EOS (AMSR-E) on board the EOS Aqua satellite.

3.1.1. Tropical Rainfall Measuring Mission (TRMM) and Global Precipitation Measurement (GPM) mission

TRMM, co-launched by NASA and Japan Aerospace Exploration Agency (JAXA) in 1997, is the first space-based rainfall that aims to observe precipitation in tropical and subtropical regions of our planet. It used both active and passive microwave instruments to measure rainfall (Grecu, Olson, & Anagnostou, 2004; Huffman et al., 2007; Iguchi, Kozu, Meneghini, Awaka, & Okamoto, 2000). Precipitation Radar (PR) was used to capture the storm structure and provided information on intensity and distribution of the rain, rain type, and storm depth and so on. TRMM Microwave Imager (TMI) is used to measure microwave energy emitted by the Earth and its atmosphere to quantify the water vapor, the cloud water, and the rainfall intensity in the atmosphere. TRMM has demonstrated significant ability to provide accurate estimation of global precipitation and near real-time monitoring of hurricanes, which has been widely used for hydrological modeling and prediction, weather prediction, and other applications (Collischonn, Collischonn, & Tucci, 2008; Hrachowitz et al., 2013; Kummerow et al., 2000; Li, Ding, & Wu, 2015; Shen, Piao, Cong, Zhang, & Jassens, 2015; Tian, Peters-Lidard, Choudhury, & Garcia, 2007). TRMM officially ended on April 15, 2015.

Building on the success of the TRMM, Global Precipitation Measurement (GPM) project is initiated by NASA and JAXA in 2014 as an international network for precipitation observations (Kidd & Levizzani, 2011; Yong et al., 2015). It is developed as in international collaboration of space agencies, including the Centre National d’Études Spatiales (CNES), the Indian Space Research Organization (ISRO), NOAA, the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), and others. The aim of the project is to develop a next-generation space-based measuring system to provide frequent, global, and accurate precipitation observations (Hou et al., 2014). The GPM constellation comprises GPM core observatory, NOAA 18/19, GCOM-V1, JPSS-1, DMSP F17/F18 (Draper, Newell, Wentz,
Krimchansky, & Skofronick-Jackson, 2015). The heart of the GPM satellite is GPM Core Observatory, a global successor to TRMM, co-launched by NASA and JAXA in 2014. GPM Core Observatory is the central rain-measuring observatory, which carries two sensors, one is DPR, a dual frequency precipitation radar (PR), and the other is GMI, a high-resolution, multichannel passive microwave (PMW) rain radiometer. GPM is served as a flagship satellite mission all over the world and has shown the importance of providing global, high-quality precipitation measurement. It has been involved in a wide range of water-related research and applications.

### 3.2. Snow and ICE

Snow and ice store about one-sixth of water in hydrological cycle and the fluctuations in the quantity and snowmelt timing of Earth's ice sheet affect the atmosphere–land surface interactions, global hydrological cycle, and sea level that may have considerable economic consequences (Day, 2007; Lee et al., 2017; Meier, 1993; Van Tricht et al., 2016). Hence it is essential to acutely monitor the snow cover and so as to understand the relationship of environmental change and snow (Robinson, Dewey, & Heim, 1993). Satellite remote sensing has proved to be a useful tool to measure snow equivalent (SWE) particularly for those areas that are inaccessible (Kääb, 2005).

Microwave sensors, including passive and active microwave sensors, have widely been applied to retrieve SWE (König, Winther, & Isaksson, 2001). Passive microwave sensors derived SWE is limited to the coarse spatial resolution and is suffered from the signal saturation due to deep snowpack, like the Arctic (Cordisco, Prigent, & Aires, 2006; Dong, Walker, & Houser, 2005; Tang et al., 2009). Satellites carrying active microwave radars, like ERS satellites’ altimeter and Synthetic Aperture Radar (SAR) approach provides much higher resolution SWE, however, they still have the limitations similar to passive microwave sensors (Eldhuset, Andersen, Hauge, Isaksson, & Weydahl, 2003).

#### 3.2.1. Ice, Cloud, and land Elevation Satellite (ICESat) & ICESat-2 missions

ICESat and ICESat-2 are two of NASA's scientific satellite missions aims to detect ice sheet mass balance, cloud and aerosol heights, as well as land topography and vegetation characteristics (Petty, Markus, & Kurtz, 2017; Schutz, Zwally, Shuman, Hancock, & DiMarzio, 2005). ICESat was launched in 2003 and ended in 2010, and as a follow-on mission, ICESat-2 is planned for launch in 2018.

ICESat was equipped with the Geoscience Laser Altimeter System (GLAS) on board that was the first polar-orbiting space borne laser altimeter system comprising three lasers (Laser 1, Laser 2, and Laser 3), a global positioning system (GPS) and a star tracker (ST) (Abshire et al., 2005). From 2003 to 2009, ICESat carried out 19 campaigns and has provided nearly continuous ice data, topography and vegetation data with unprecedented vertical and angular resolution. The GLAS data are widely used to in various fields, like detecting the sea-ice freeboard and thickness, capturing the changes of glaciers and ice caps, extracting the sub-glacier water system, observing the changes of water level, etc.

Based on the success of ICESat, NASA ICESat-2 is scheduled to continue the ICESat observations (Abdalati et al., 2010). Compare to ICESat, ICESat-2 makes considerable progress in the instrument it carries on board that is an Advanced Topographic Laser Altimeter System (ATLAS) (Petty et al., 2017). It is a multi-beam, photon-counting laser altimeter, with six linear
profiling beams that scan a total width of 6 km (Markus et al., 2017). Such an instrument will improve the spatial coverage of the satellite data, which is about 9 times larger than that of ICESat satellite. Therefore, the observations provided by ICESat-2 will benefit snow and ice research and advance our knowledge about the cryosphere (Petty et al., 2017).

### 3.2.2. CryoSat-2 mission

CryoSat-2 is ESA's first mission for ice monitoring (Drinkwater, Francis, Ratier, & Wingham, 2004; Laxon et al., 2013; Wingham et al., 2006). CryoSat-2 was launched in April 2010 by ESA, whose primary purpose is to monitor Arctic sea ice thickness and is then prove to be useful to provide continuous observations of Earth's land and marine ice flux (Jiang, Nielsen, Andersen, & Bauer-Gottwein, 2017; Wingham et al., 2006). CryoSat-2 satellite has marked a new era in radar altimetry as it carries a state-of-the-art single Ku-band radar altimeter, namely Synthetic Aperture Interferometric Radar Altimeter (SIRAL) (Villadsen, Andersen, Stenseng, Nielsen, & Knudsen, 2015). Apart from the Low-Resolution Mode (LRM) that is equivalent to conventional radar altimetry such as Envisat, CryoSat-2 also works in high-resolution mode including SAR and SAR Interferometer (SARIn). The SAR mode highly promotes the spatial resolution which is used over coastal regions. SARIn modes is designed for the mountainous areas such as measuring the mountain glaciers. CryoSat-2 has demonstrated great potential for monitoring surface water (Göttl, Dettmering, Müller, & Schwatke, 2016; Nielsen, Stenseng, Andersen, Villadsen, & Knudsen, 2015; Villadsen et al., 2015), sea ice (Calafat, Cipollini, Bouffard, Snaith, & Féménias, 2017; Kurtz, Galin, & Studinger, 2014; Kwok, 2014; Ricker, Hendricks, Helm, Skourup, & Davidson, 2014; Schroeder, Tsamados, Feltham, Tilling, & Ridout, 2017; Xia & Xie, 2018), glaciers (Gower, 2017; Helm, Humbert, & Miller, 2014; McMillan et al., 2014; Wouters, Noël, Moholdt, Ligtenberg, & van den Broeke, 2017).

### 3.3. Evapotranspiration

Evapotranspiration (ET) transfers a large amount of water from land surface into atmosphere, which is also closely associated with land surface–atmosphere exchanges of carbon, and energy (Courault, Seguin, & Olioso, 2005; Wang & Dickinson, 2012). Reliable ET measurements are vital to better understand global water balance and terrestrial ecosystems. Numerous approaches are established to retrieve ET from satellite observations (Dugo & Gao, 2011; Kalma, McVicar, & McCabe, 2008; Liou & Kar, 2014; Mercado et al., 2009; Miralles et al., 2016; Su et al., 2010), such as One-source model (Bastiaanssen, Menenti, Feddes, & Holtslag, 1998; Jaber, Mansor, Pradhan, & Ahmad, 2016), Two-source model (Anderson & Kustas, 2008; Li et al., 2008; Yang et al., 2015), Penman–Monteith equation (Cleugh, Leuning, Mu, & Running, 2007; Mu et al., 2011). Those methods can be summarized into three groups. One is empirical or statistical methods, which link measured ET with vegetation derived from remote sensing (Glenn, Huete, Nagler, & Nelson, 2008; Jung et al., 2010). The second one is based on surface energy balance using satellite-based surface temperature (Ts) which is called thermal infrared algorithms, like Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998), ALEXI (Anderson et al., 1997), SEBS (Su, 2002), METRIC (Allen, Tasumi, Morse, & Trezza, 2005). The third one is based on the Penman–Monteith equation with the satellite-based inputs (Cleugh et al., 2007; Mu, Heinsch, Zhao, & Running, 2007; Mu, Zhao, & Running, 2011; Vinukollu, Wood, Ferguson, & Fisher, 2011).
3.3.1. **Terra and aqua moderate-resolution imaging spectroradiometer (MODIS)**

MODIS is one of the most practical missions for ET estimation. Terra satellite was launched in 1999 while Aqua satellite was launched in 2002. The two satellites are viewing the entire Earth’s surface every 1 to 2 days, acquiring data in 36 spectral bands, or groups of wavelengths with three spatial resolutions: 250, 500 m, and 1000 m. 

MOD 16 is a global terrestrial ET products, released by the LP DAAC, providing global ET, latent heat flux (LE), potential ET (PET), and potential latent heat flux (LE) of the major terrestrial area from 2000 through 2010 with a spatial resolution of 1 km² and a temporal resolution of 8 days (Mu, Zhao, & Running, 2013). Such data-set has made Earth system models able to predict global change accurately enough to assist policy-makers in making sound decisions concerning the protection of our environment (Cleugh et al., 2007; Hu, Jia, & Menenti, 2015; Liu, Xu, Zhu, Jia, & Zhu, 2013; Tang et al., 2015; Velpuri, Senay, Singh, Bohms, & Verdin, 2013).

3.4. **Soil moisture**

Soil moisture is a key component determines the Earth’s water, energy and carbon cycle, and also impact weather and climate (Houser et al., 1998; Mohanty, Cosh, Lakshmi, & Montzka, 2017). Since the late 1970s, numerous soil moisture products have been derived from microwave sensors. Low frequencies (X, C, and L bands) have been applied to retrieve bare or vegetated soil water content. The C and X band (with a frequency of 6–11 GHz) sensors onboard a wide range of satellites, such as AMSR-E, SCAT, RADASAT, have shown great importance in global soil moisture estimation (Jackson, 1993; Njoku & Entekhabi, 1996; Wang & Qu, 2009). Newer sensors have equipped with lower frequency (L band), such ESA Soil Moisture and Ocean Salinity Mission (SMOS) (Kerr et al., 2001) and NASA Soil Moisture Active Passive Mission (SMAP), allowing deeper penetration depth, which have bring the soil moisture measurement into a new dimension.

3.4.1. **Soil Moisture and Ocean Salinity (SMOS) mission**

SMOS mission, launched on 2 November 2009, is ESA’s second Earth Explorer Opportunity mission in orbit, which is part of ESA’s Living Planet Program (Font et al., 2010; Kerr et al., 2001; Kerr et al., 2010). It is the first satellite mission aims to provide global soil moisture over land and sea surface salinity over ocean from space. The SMOS satellite carries a novel interferometric radiometer named Microwave Imaging Radiometer with Aperture Synthesis (MIRAS) (Corbella et al., 2005). The instrument operates in the L-band microwave range at 1.4 GHz. After 4 years in orbit operation, a large amount of data have been sent back to derive global maps of soil moisture every three days, achieving an accuracy of 4% at a spatial resolution of about 50 km.² The SMOS data are now are widely used contributing fundamental understanding of the global water cycle, climate change and oceanic currents (Al Bitar et al., 2012; Al-Yaari et al., 2014a, 2014b; Dohan & Maximenko, 2010; Lacava et al., 2012).

3.4.2. **Soil Moisture Active Passive (SMAP) mission**

SMAP mission, launched in 31 January 2015, is NASA’s Earth observation satellite dedicated to retrieve continuous global soil moisture and its freeze/thaw state from space (Brown et al., 2013; Entekhabi et al., 2010). SMAP is one of four first-tier missions recommended by the
National Research Council’s Committee on Earth Science and Applications from Space (Board & National Research Council, 2007).

The accuracy, spatial resolution and global coverage of SMAP soil moisture data are unprecedented. To overcome the limitation of coarse spatial resolution of passive sensor-based observation, SMAP carries both active and passive instruments onboard, an active L-band radar and a passive L-band radiometer. The radiometer provides soil moisture with high soil moisture accuracy with coarse spatial resolution (approximately 40 km), while the radar yields high resolution (1–3 km) with lower soil moisture accuracy. Thus, by combining measurements from the two sensors, it is possible to gain a both high spatial resolution and high accuracy soil water content data (Kerr et al., 2012). Although only been in orbit for three years, SMAP have demonstrated impressive and incredible capabilities to retrieve soil moisture, which have been invaluable information for hydrology, climate, energy cycle and carbon cycle, etc. (Chan et al., 2016; Das et al., 2014; Panciera et al., 2014; Piles, Entekhabi, & Camps, 2009; Piles et al., 2011).

3.5. Streamflow

Streamflow is a critical water cycle component which plays important role for water resources management and also for hydrological modeling. Unfortunately, our knowledge about the surface water storage is extremely limited as the regular gaging stations is sparse on spatial. Although satellite remote sensing has been used to calculate the surface area of rivers or lakes, so far, no ongoing mission is possible to monitor streamflow discharge on global or regional scales. These limitations have led to the development of remote sensing streamflow observations (Bates, Neal, Alsdorf, & Schumann, 2014; Venkat, 2016; Wood et al., 2011). Such situation will be relieved as many future missions, like CRYOSAT 2, SWOT are planned to launch setting to estimate the global and regional water discharge.

3.5.1. Surface Water & Ocean Topography (SWOT) mission

The SWOT mission, planned to launch in April 2021, is a joint space mission of NASA, a French space agency CNES, and some other space agency such as Canadian Space Agency (CSA) and UK Space Agency (UKSA) (Durand et al., 2010; Fu et al., 2009). It will be the first mission that makes a global survey of the Earth’s surface water and observes the topography of the ocean, and measures the change of water level.

The SWOT satellite will carry Ka-band Radar Interferometer (KaRIN), a new type of radar instrument, which implements two Synthetic Aperture Radar (SAR) antennas (Rodriguez & Esteban-Fernandez, 2010). It will provide unprecedented high resolution to derive surface water height, 50 m for terrestrial water bodies and 1 km for ocean. Despite for the high resolution, it is also expected to obtain water discharge with high accuracy, about 1 cm averaged over 1 km² across a 120-km swath (McCabe et al., 2017). Such data, combining with hydrological model, could contribute significantly to large-scale watershed management, flood monitoring, water stage variation related to climate change, etc., (Biancamaria et al., 2016; Calmant, Seyler, & Cretaux, 2008; Dohan, 2017).
3.6. Groundwater and water storage

3.6.1. Gravity Recovery and Climate Experiment (GRACE) mission
With the launch of the GRACE, it is possible to obtain the groundwater and water storage (Tapley, Bettadpur, Ries, Thompson, & Watkins, 2004). Since 2002, NASA and the German Aerospace Center have co-launched two twin satellites of GRACE, which have been so far, the only space-based mission capable of measuring the mass variation of the Earth system. By measuring the distance between the two satellites, GRACE retrieves global Earth's gravity field, using with GPS and a microwave ranging system. The gravity field data are then used to estimate the global snow, surface water, soil moisture, groundwater, and water storage.

GRACE is unique in monitoring water at all levels and have proved to be efficient and cost-effective way for mapping global groundwater and terrestrial water storage. Such data have been the critical information for land surface model construction and evaluation, Ei Nino and La Nina phenomes analysis, water budget analysis, etc., (Bhanja, Mukherjee, Saha, Velicogna, & Famiglietti, 2016; Döll, Müller Schmied, Schuh, Portmann, & Eicker, 2014; Reager, Thomas, & Famiglietti, 2014; Tapley et al., 2004). However, the GRACE is highly subjected to the limitations including coarse spatial resolution (>150,000 km²), low temporal resolution (monthly) and data latency (typical 2–4 month). GRACE follow-on has been launched in 2017, which has greatly improved the spatiotemporal resolution of the data (Flechtner, Morton, Watkins, & Webb, 2014).

3.7. Integrated water cycle monitoring

Most of the ongoing missions focus on one aspect element of water cycle without taking into account the environmental variable or other support information which are also need for the target element estimate (Shi et al., 2016). For example, for soil moisture observations, L-band radiometer is widely used which is incapable of providing the information like vegetation condition. This limitation lead to the launch of Water Cycle Observation Mission (WCOM).

3.7.1. Water Cycle Observation Mission (WCOM)
China will launch WCOM around 2020, aiming to provide integrated, high accuracy and consistent measurement of key components of water cycle, including precipitation, atmospheric water vapor, snow water equivalent, soil moisture, soil freeze-thaw, snow water equivalent, and other associated variables (Shi et al., 2014, 2016).

WCOM will be the first mission that carries innovative payload combining active and passive microwave sensors with wide frequency, including an L-S-C tri-frequency Full-polarized Interferometric synthetic aperture microwave Radiometer (FPIR) with 15–20 km spatial resolution, a Polarized Microwave Radiometer Imager (PMI) with 4–50 km spatial resolution, and an X-Ku Dual-Frequency Polarized SCATterometer (DFPSCAT) with a 2–5 km spatial resolution. Through such instruments, it is expected that the WCOM will send back accurate and consistent data for hydrologic science.
4. Fourth paradigm for hydrology: opportunities and challenges

The hydrologic science has evolved from empiricism (first paradigm), via theory (second paradigm) to computational simulation (third paradigm) (Peters-Lidard et al., 2017). The exposition of Earth observation data have provided the opportunities for hydrologic science to no longer rely on the traditional approach. The hydrology is on the threshold of fourth paradigm, data-intensive science (Figure 3).

Although big data promise to help provide new insights for understanding hydrological processes, hydrology is facing with a great number of challenges for the following reasons. First of all, as one of the branch of big data, Earth observation data have their own 4 V feature including volume, variety, veracity, and velocity. Almost all Earth observation sensors collect gigabyte data on daily basis and some can even exceed terabyte. Terabyte and petabytes data will be handled for continental or global-scale applications. To process such large data volume will be impossible with the traditional computing resources. In addition, as data are obtained from multiple sources, different data type and scales will make data aggregation extremely difficult. The traditional data processing and analysis approaches can’t meet the computing requirement. Secondly, Earth observation data have unique 3H connotations that is high dimension, high complexity, and high uncertainty (Guo et al., 2014). The 3H connotations make it daunting to gain valuable information from Earth observation big data.

Figure 3. An illustration of scientific methods of hydrology and paradigms (Peters-Lidard et al., 2017).
data. The traditional algorithms are no longer suitable for application of EO big data in hydrology.

Efforts have been paid to process and analysis the Earth observation data in hydrology. IT technology such as high-performance computing borrowed from the computer science and data science are applied to address the huge data volumes and the increasing complexity of Earth observation data. We here identify the important and emerging issues in applying Earth observation data for hydrological research.

4.1. Cloud computing

Cloud computing is a new evolution in computing, which is defined National Institute of Standards and Technology (NIST) as “a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g. networks, servers, storage, applications, services) that can be rapidly provisioned and released with minimal management effort or service provider interaction”. Cloud computing has become a hot topic and is the top of technology trend in recent years. Companies, like Amazon, Google, IBM, Microsoft, have established data centers for cloud computing applications (Hashem et al., 2015).

In the field of Earth observation, cloud computing has already been adopted for data storage, processing and analysis. For instance, NASA shared Earth Science “Big Data” (climate and Earth science satellite data) to research and educational users through the Amazon Web Services (AWS) cloud. The service includes selected NASA satellite and global change data-sets, data processing tools from the NASA Earth Exchange (NEX) and a research platform NASA Advanced Supercomputer Facility. In 2016, Amazon Web Services (AWS) launched Earth on AWS which specifically provide cloud service for geospatial data-sets, where users can build planetary-scale applications in the cloud with open geospatial data. Google has built an advanced cloud platform called Earth Engine, which offers storage and computing resources for geospatial data-sets (Gorelick et al., 2017).

Given the challenges associate with big Earth observation data applications in hydrology, scientists have begun to adopt cloud computing for multiple source data integration, data storage, and data processing, etc. A handful cloud platforms have been built, such as Earth Observation Data for Water Resources Monitoring (EODC), HydroCloud (McGuire, Roberge, & Lian, 2014). We will present as follow the EODC as a representative. EODC is a cloud platform supporting using Earth observation data for monitoring global water resources. It operates a virtualized, distributed EO data center, connected to ESA’s data hubs to receive EO data including Sentinel 1, Sentinel 2, and Sentinel 3. It provides IT infrastructure to archive, process and distribute the in-coming EO data. A broad range of water cycle elements, like soil moisture, flooding, water body, can be observed or estimated from satellites by the cloud platform. This work is still in the start-up stage, and some of the capacities are still under developing, such as the capacity for receiving and processing the near-real-time data. Regarding the dramatically increase of EO data, the requirement of cloud computing for near-real-time EO data storage, processing and analysis in hydrology will be a big challenge.
4.2. Data-driven modeling and artificial intelligence techniques

Big Earth data have hidden high value which reveal insight of hydrological science. However, facing with a huge amount and a wide variety of EO big data, it is a big challenge to exploit valuable information and knowledge from the data. Traditionally, hydrological models which are established based on the hydrologic processes are the core method for research, applications, and for knowledge discovery. However, when we turn to the massive data-sets, the traditional models become powerless as the original model structure or theory are ill-designed or incomplete. Data-driven modeling techniques and artificial intelligence techniques that have been developed in data science will be an alternative for EO big data utilization in hydrology.

Data-driven modeling and artificial intelligence techniques have been applied in hydrology for nearly three decades (Elshorbagy, Corzo, Srinivasulu, & Solomatine, 2010). A wide variety of techniques are in use, such as Artificial Neural Networks (ANNs), Genetic Programming (GP), Support Vector Machine (SVM) model. A great number of studies have been reported targeting the rainfall-run-off, evapotranspiration, soil moisture modeling using monitoring data. With respect to the EO data, most of the efforts are paid on hydrological flux retrieval and prediction with single or multiple satellites data. For example, Chen, Yeh, Wei, and Liu (2011) used GP method to estimate typhoon rainfall with special sensor microwave imager (SSM/I). Rodríguez-Fernández et al. (2016) applied a neural network (NN) to derived soil moisture (SM) from Advanced Scanning Microwave Radiometer – Earth Observing System Sensor (AMSR-E) observations using Soil Moisture and Ocean Salinity (SMOS). Those attempts have demonstrated the potential of data-driven modeling and artificial intelligence techniques for EO observation big data applications in hydrology.

4.3. Quantification of uncertainty in EO big data

Big data are characterized by low veracity and high uncertainty which is especially true for Earth observation data. Due to the limitations in measurement instruments and data processing technologies, Earth observation data are suffered from uncertainty, errors, noise and large-scale missing. What make things worse is that the errors in Earth observation data remain unknown. The question with how good is a particular Earth observation data is difficult to answer. It is a challenge task to adequately characterize uncertainty and trace the uncertainty associated with EO big data. In addition, some traditional data analysis and learning algorithms are obviously not valid to process such kind of data. For example, most of the traditional data analysis methods are incapable to deal large-missing data. How to deal with different uncertainty and errors of different EO big data is particularly important before using them.

Different methods and approaches have been developed to address the uncertainty problem in Earth observation community. For example, variable-specified validation protocols and frameworks are established to trace the uncertainties.

In the field of hydrology especially hydrologic modeling, there are many new and developing perspective on how to estimate uncertainty. Given the different uncertainty sources including input data, model structure and parameters, different probabilistic techniques have been developed to estimate uncertainty, such as Generalized Likelihood Uncertainty Estimator (GLUE) (Beven & Freer, 2001), Markov chain Monte Carlo (MCMC) (Jeremiah,
Sharma, Sisson, Marshall, & Mehrotra, 2011; Smith & Marshall, 2008), data assimilation (DeChant & Moradkhani, 2011; Moradkhani, 2008). Among these approaches, data assimilation have been proved to be an attractive method for handling the uncertainty from EO data and for improving hydrologic predictions as demonstrated in numerous studies. However, when the data volume highly increases, the traditional data assimilation approaches will not suitable, which should be a question for the future study.

5. Conclusions and recommendations

With the increasing awareness of the importance of hydrologic science and water cycle, a wealth of satellite missions for hydrologic observation are launched by space agency, which have led to a big data era for hydrology. This review illustrates the existing and ongoing Earth observation missions for hydrologic sciences. For different water cycle elements and processes, different missions are launched to specify and characterize the hydrological variables. Hydrology have entered a new big data era and it is time for hydrology to shift to the fourth paradigm for hydrology, data-intensive science. There are certainly challenges in applying the emerging Earth observation big data in hydrology. The new technologies developed in the field of information and data science, could be borrowed to address the challenges. It is our hope the Earth observation big data will open a new vision the hydrology.

Data availability statement

Not applicable for Review Article.

Notes

1. https://open.nasa.gov/blog/what-is-nasa-doing-with-big-data-today/.
2. http://www.taikongmedia.com/Item/Show.asp?m=1&d=23633.
3. http://www.esa.int/Our_Activities/Observing_the_Earth/SMOS/Facts_and_figures.
4. https://www.nist.gov/news-events/news/2011/10/final-version-nist-cloud-computing-definition-published.
5. https://www.nasa.gov/press/2013/november/nasa-brings-earth-science-big-data-to-the-cloud-with-amazon-web-services/#.Wka9FPmnG71.

Disclosure statement

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