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Key Points:
- Satellite remote sensing is being incorporated into water resources management but is generally underutilized
- New and proposed missions have the potential to transform water resources management for sustainable development, especially in data-poor regions
- Ongoing challenges of accuracy, sampling, and continuity and capacity development need to be addressed, as well as new challenges of information volume and diversity

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Satellite Remote Sensing for Water Resources Management: Potential for Supporting Sustainable Development in Data-Poor Regions

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Abstract Water resources management (WRM) for sustainable development presents many challenges in areas with sparse in situ monitoring networks. The exponential growth of satellite based information over the past decade provides unprecedented opportunities to support and improve WRM. Furthermore, traditional barriers to the access and usage of satellite data are lowering as technological innovations provide opportunities to manage and deliver this wealth of information to a wider audience. We review data needs for WRM and the role that satellite remote sensing can play to fill gaps and enhance WRM, focusing on the Latin American and Caribbean as an example of a region with potential to further develop its resources and mitigate the impacts of hydrological hazards. We review the state-of-the-art for relevant variables, current satellite missions, and products, how they are being used currently by national agencies across the Latin American and Caribbean region, and the challenges to improving their utility. We discuss the potential of recently launched, upcoming, and proposed missions that are likely to further enhance and transform assessment and monitoring of water resources. Ongoing challenges of accuracy, sampling, and continuity still need to be addressed, and further challenges related to the massive amounts of new data need to be overcome to best leverage the utility of satellite based information for improving WRM.

1. Introduction

Water resources management (WRM) is a key global challenge. Water is essential to life through drinking water and sanitation and is fundamental to the provision of food, energy, and health. Extremes of the water cycle (floods and droughts) can have tremendous impacts on all human activities, especially for vulnerable populations. Water is therefore of central importance to development and has been recognized as one of the United Nations (UN) Sustainable Development Goals (SDGs; UN, 2015): SDG6 Clean water and sanitation. Addressing water challenges to the provision of clean water and protection from water hazards will help address many of the other SDGs, particularly for food security (SDG2: Zero hunger), public health (SDG3: Global health and well-being), and poverty alleviation (SDG1: No poverty; Grey and Sadoff, 2007). Since the early civilizations when water was first managed for public benefit, there has been a revolution in management from simple storage, diversions and abstractions to mega engineering projects for water transfer (e.g., China North-South transfer project) and reservoir storage (e.g., Grand Inga Dam in the Democratic Republic of Congo). However, the equitable, efficient and sustainable provision of water still poses considerable challenges.

Lack of water is a perennial problem, through low availability of water supply and poorly managed demand for water that combines to result in water scarcity (Veldkamp et al., 2015). Water supply is primarily defined by the mean and variability of precipitation, and its translation into available water through surface water supplies and aquifer recharge, but also on how we are able to store and sustainably manage reservoirs and aquifers. Dependency of communities and nations on single sources of water (e.g., from aquifers) and upstream rivers (with or without transboundary agreements) can easily lead to short-term crises and long-term unsustainable use (e.g., Müllera et al., 2016; Munia et al., 2016; Weinthal et al., 2005), although conflict is rare (Wolf et al., 1998). Demand for water is also poorly understood and managed in many regions, in part because of lack of effective governance and institutional structures capable to equitably and sustainably balance

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competing needs with limited resources. This is set in the context of ongoing and future projected changes in supply and demand that make addressing these challenges imperative. On the supply side, climate change is expected to lead to regional changes in water resources, including declines through decreased precipitation and increased evapotranspiration (ET), especially in the subtropics, increases mainly from more precipitation, particularly in the tropics and high latitudes, and changes in seasonality, such as via earlier snowmelt linked to warming. At the same time, there is potential for increased variability in climate leading to more droughts (Sheffield & Wood, 2008). Precipitation is expected to come in fewer but more intense storms and has the potential to increase flood risk (Hirabayashi et al., 2013). On the demand side, population increase, rapid urbanization, and increased demands from agriculture and energy production are expected to lead to challenges for water quality and allocation of resources (O'Connell, 2017) that may outweigh the uncertain impacts of climate change.

Achieving water security and increased resilience to hydrological extremes requires a good understanding of water resources dynamics at the basin scale. This knowledge and understanding can only be based on data and observations, and it is the foundation for managing water optimally and efficiently in economic and social terms, as well as with regard for environmental impacts and downstream users. In particular, information is needed on hydrological variables that constitute the hydrological cycle on land, how they vary over time and space, and how they manifest in extremes and therefore hazard risk (García et al., 2016; Hering, 2014; Walker, 2000). This could be in the form of hazard monitoring and early warning to help communities prepare for potential and evolving impacts (Pozzi et al., 2013; Sheffield et al., 2014; Todini, 2017). In the context of drought, information is needed on the state of water resources (e.g., surface water such as rivers, reservoirs, and snowpack, and subsurface water: soil moisture and groundwater) as well as the related health of natural vegetation and crops. For floods, data on riverine flows and inundated areas are required to assess impacts. For early warning, short-term and seasonal forecasts of hydrologic variables and potential agricultural impacts are also necessary to provide the lead time to enact measures to reduce impacts, and these forecasts need to be initialized and verified with observational data (Sheffield et al., 2014; Tang et al., 2016; Yuan et al., 2015). At the same time, long-term, multisite time series (several decades) of relevant variables are required to estimate risk of flood/drought hazards as inputs into resource utilization and design of infrastructure for reduction of the hazard itself and mitigation of impacts (e.g., Serinaldi & Kilsby, 2016).

In many regions, hydrometeorological and agricultural monitoring networks are often sparse and have large latency and so are impractical for real-time decision-making. In developing regions where the need for information is arguably greatest, the data collection infrastructure and human capacity to monitor and forecast hazards is generally low because of the decline in hydro-meteorological and agricultural monitoring networks over the past 30 years (Lorenz & Kunstmann, 2012) and ongoing lack of investment in infrastructure and training (Fay et al., 2017).

Satellite remote sensing is increasingly being used as a complementary source of information to in situ monitoring networks and, in many cases, is the only feasible source. Satellite-based sensors are now capable of making direct and indirect measurements of nearly all components of the hydrological cycle (Lettenmaier et al., 2015; McCabe et al., 2017; Y. Zhang et al., 2016). These include precipitation, evaporation, lake and river levels, surface water, soil moisture, snow, and total water storage (surface and subsurface water). These sensors are therefore capable of providing critical information in support of managing water and monitoring the evolution of hazards and their impacts (van Dijk & Renzullo, 2011). There is also a long legacy of remote sensing retrievals of the variation in vegetation state and thus plant productivity and health, with applications in agricultural monitoring and planning. The large coverage (up to global) of satellite data also enables the assessment of risk in the context of regional water security, food production, storage, and trade (e.g., Dalin et al., 2017; Jones et al., 2009). Although some of these satellite remote sensing products are in their infancy, and there are significant limitations, challenges, and caveats in their use for WRM, the large spatial coverage and high temporal resolution (subdaily for geostationary and equatorial orbiting satellites) means that they can provide near-global information in near real time.

This paper provides an overview of the current and potential future role of satellite remote sensing in improving WRM, with a focus on examples for Latin America and the Caribbean (LAC). Our discussion is applicable to other developing regions where improved WRM would help deliver the SDGs, but where this is hampered by lack of in situ data. The paper is a contribution to activities by the Inter-American Development Bank to improve management and planning of water resources in the LAC region. The LAC region includes a wide range of climatic and hydrologic regimes and is thus confronted with a broad range of management challenges and the need for an integrated approach to support WRM. The population is unevenly distributed and access to clean water and sanitation is inequitable, particularly in large urban areas. The LAC met the Millennium Development Goal for drinking water ahead of schedule, with 95% coverage by 2015. Progress toward halving the number of people without access to basic sanitation was less successful, with access increasing from 67% in 1990 to 83% in 2015 (UN, 2015). Projections for the SDG Goal 6.1 of universal access to sanitation indicate that while about a quarter of countries are on track, several countries in the Caribbean are projected to make no progress at all, and rates of progress have to increase by several times in many countries (Nicolai et al., 2016). Improved water management also plays a crucial role in achieving many other SDGs, most directly for agricultural (SDG2) and energy production (SDG7), and hydrological hazards (SDG6 and SDG13), and also those related to poverty (SDG1), education (SDG4), and child mortality (SDG3), for example (Inter-American Development Bank, 2005). The continent is also playing a larger role in agricultural production and global food security, which requires careful water management to optimize trade-offs with environmental impacts (Flachsbarth et al., 2015). In turn, addressing other SDGs, such as inequality, will help achieve the water-related SDGs.

The LAC region represents a diverse set of contexts in terms of monitoring networks, information sharing, and capacity to manage resources (Donoso & Bosch, 2012), which is in part due to gaps and fragmentation in water governance across sectors and levels (Akhmouch, 2012) and problems in developing and financing infrastructure (Fay et al., 2017). The region represents diversity in how water policy is governed and resources are managed with a tendency overall to have decentralized governance, which is typical of more developed countries, and also a relatively larger role of central government. However, the region would benefit from greater intersectoral coordination, capacity building, and governance across levels that is flexible and especially targeted at the poor (Akhmouch, 2012). Furthermore, climate change has the potential to exacerbate water resources challenges and natural disaster impact mitigation, with expected regional changes in available water, particularly through impacts on glaciers and seasonal snow, and increases in floods and drought severity and frequency (Reyer et al., 2017).

The exponential growth of satellite-based information over the past decade, through increased numbers of satellites launched with ever increasing resolution, and multiple derived products, provides unprecedented opportunities to support and improve WRM in the LAC region and worldwide. Furthermore, traditional barriers to the access and usage of satellite data are lowering as technological innovations provide opportunities to manage and deliver this wealth of information to a wider audience. Nevertheless, ongoing challenges of accuracy, sampling and continuity still need to be addressed, and new challenges are presented by this wealth of new data that need to be overcome to best leverage the utility of satellite based information for improving WRM. Here we review data needs for WRM and the role of remote sensing (RS), particularly in regions of sparse in situ data (section 2). In section 3 we review the state-of-the-art for relevant variables, current satellite missions and products, and the challenges to improving their utility. An overview of current use of RS in the LAC region for decision-making is also provided. We discuss upcoming and proposed missions in section 4, and the opportunities and challenges of RS for WRM in section 5.

2. Data Needs for WRM

WRM entails the efficient and sustainable use of water resources for beneficial use and environmental protection (Loucks, 2009). In practice, this covers a range of activities from operational management of existing resources, development of new resources, and planning and design of associated infrastructure, as well as early warning of hydrological hazards and management and reduction of risks. To this end, information on resources and hazard risk is essential. WRM also includes issues related to administration and governance, although these are not discussed here.

There are a range of WRM decisions that benefit from hydrometeorological information, as well as land cover and use. These include land management and water allocation at the basin scale for an array of interrelated sectors (agriculture, ecosystems, forest management, energy production, water supply, etc.); environmental management and protection; the design and operation of water infrastructure for hydropower, flood control, drought preparedness and mitigation, irrigation, water supply, and wastewater treatment; management of

Table 1
Summary of WRM Decisions, the Data Products Required to Make These Decisions, and the Traditional Sources of Such Data (based on García et al., 2016)

Water resources management decision	Water-related data products used to make decision	Traditional data sources
Planning and design		
Design of flood control (design of flood storage, routing, and alleviation)	Long-term records (decades) of precipitation and streamflow; long-term records of SWE in cold regions	Rain gauge networks; stream gauge networks; snow courses and pillows
Design of hydropower systems (for reliable power production given available resources)	Long-term records (decades) of streamflow; long-term records of SWE in cold regions	Rain gauge networks; stream gauge networks; snow courses and pillows
Design of irrigation systems (including extraction and distribution and water use)	Long-term records (decades) of precipitation, streamflow and groundwater. Estimates of crop water use	Rain gauge networks; stream gauge networks; wells, piezometers; meteorological networks
Design of wastewater treatment systems (capture, treatment, reuse, and release)	Records of feed sources such as streamflow and groundwater	Stream gauge networks; wells, piezometers
Design of water supply systems (for effcient supply of desired quality water)	Records of precipitation, streamflow, and groundwater	Rain gauge networks; stream gauge networks; wells, piezometers
Transboundary water agreements (to understand use and needs and to design agreements and management strategies)	Long-term (decades) streamflow and groundwater records; water use records	Stream gauge networks; wells, piezometers
Management and operations		
Water resources management (to satisfy water demand given supply)	Real-time precipitation, evapotranspiration, streamflow, and groundwater	Rain gauge networks; eddy-covariance towers; stream gauge networks; wells, piezometers
Water supply operations (to ensure reliable water supply)	Real-time precipitation, evapotranspiration, and groundwater	Rain gauge networks; eddy-covariance towers; stream gauge networks; wells, piezometers
Hydropower operations (maximize power production under other constraints)	Real-time precipitation, evaporation, streamflow, precipitation forecasts	Rain gauges; stream gauges; meteorological stations; weather forecasts
Flood control operations (reservoir operation to regulate and dampen floods)	Real-time precipitation, streamflow and snow water equivalent, precipitation forecasts	Rain gauges; stream gauges; snow courses and snow pillows; weather forecasts
Wastewater management (efficient treatment, reuse, and disposal)	Real-time streamflow and groundwater data	Stream gauges; wells, piezometers
Irrigation systems operation (efficient extraction and distribution of water to meet crop water needs)	Real-time precipitation, streamflow, groundwater, and soil moisture. Estimates of evapotranspiration	Rain gauge networks; stream gauge networks; wells, piezometers; soil moisture probes; eddy-covariance towers; meteorological stations
Ecosystem management (to maintain ecosystem services)	Recent data on precipitation, streamflow, water levels, soil moisture, water quality	Rain gauges; stream gauges; stage gauges; water quality sampling
Disaster Management		
Crop monitoring and food security (monitor food production and availability; early warning of food insecurity and famine)	Real-time vegetation characteristics, crop water needs, soil moisture, precipitation forecasts	Field crop sampling; eddy-covariance towers; meteorological stations; soil moisture probes; weather forecasts
Drought early warning and management (mitigate risk and manage impacts)	Real-time precipitation, soil moisture, streamflow, groundwater, precipitation forecasts	Rain gauges; soil moisture probes; stream gauges; wells, piezometers; weather forecasts
Flood early warning and management (mitigate risk and manage impacts)	Real-time precipitation, streamflow, precipitation forecasts	Rain gauges; stream gauges; weather forecasts
Water-related health (monitoring and managing water quality, pollution, disease vectors)	Real-time precipitation, surface water, water quality parameters	Rain gauges; stream gauges; stage gauges; water quality sampling

water for agriculture, energy production, industry, forest and range management, and health applications; hydrological disaster risk management and reduction; and broader issues related to water resources development, planning policy, and governance (García et al., 2016). Table 1 provides a summary of the main WRM decisions, the types of variables required, and how these are obtained traditionally. In addition, there are many other decisions that require information on water related variables, such as land use planning and environmental planning and management that are not covered here.

The main variables considered here as useful for WRM are precipitation, ET, vegetation indices, streamflow, soil moisture, groundwater (including recharge and levels), snow (extent and snow water equivalence, SWE), soil ice, and water quality. Supporting meteorological information (temperature, wind speed, surface radiation, etc.) and physiographic information (land cover change, topography [elevation and aspect], soils,

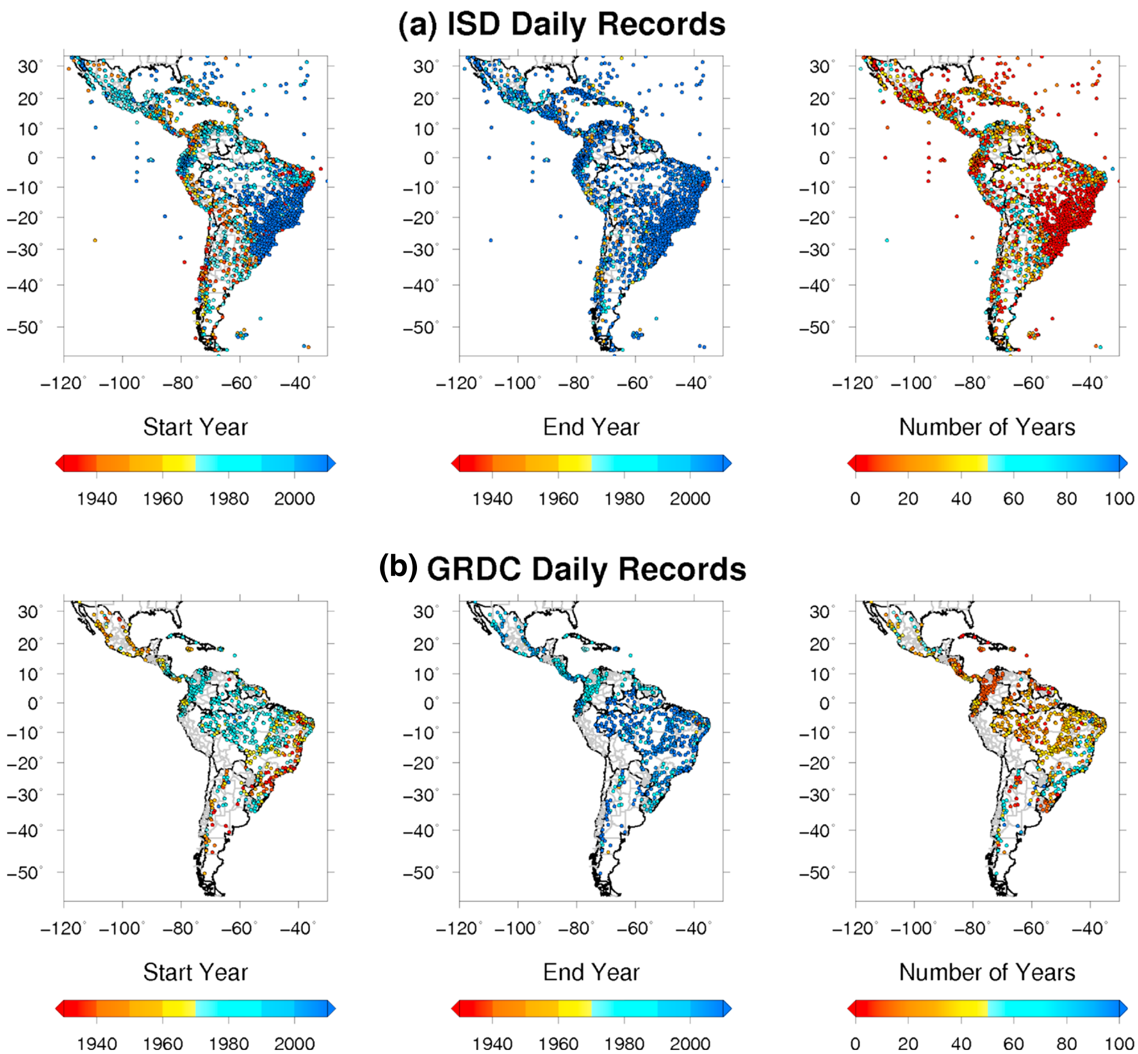

Figure 1. Distribution of record start year, end year, and total number of years for (a) precipitation from the Integrated Surface Database (ISD) database and (b) streamflow from the Global Runoff Data Centre (GRDC) database. The ISD (Smith et al., 2011) consists of global hourly and synoptic observations from over 35,000 stations worldwide. The GRDC (2018) is an international archive of river discharge data for more than 9,500 stations in 160 countries.

etc.) are also useful or essential. Knowledge of these variables enables an understanding of the hydrological cycle over a region and how it interacts with different uses and sectors. In particular, it is important to quantify existing water resources in relation to current demand and sustainable development of resources in the context of future demand, where demand also includes the needs of other sectors, in particular natural ecosystems. For example, groundwater is an essential resource in many regions, to enable development or gain resilience by diversifying sources. However, knowledge of the sustainability of these resources is often lacking but is imperative if they are to be beneficial to current and future generations. Each of these variables plays a role in the terrestrial hydrological cycle either as a driver (e.g., precipitation), a feedback (e.g., ET), or a state (e.g., soil moisture and snow) that also acts as a mediator of the various fluxes (e.g., soil moisture controls on ET). The connectivity between these variables and propagation of anomalies through the hydrological system (e.g., the propagation of drought) is one of its key features that has implications for how resources are managed within river basins, implying that management based on individual variables is unlikely to be optimal.

The wealth of in situ observations in some parts of the world is sometimes sufficient to manage and plan water resources; for example, in the United States the extensive (in time and space) network of river gauging stations in some regions is generally sufficient to quantify renewable resources based on surface water, but the lack of in situ information on ET or snowpack means that upstream changes in resources, land cover/use,

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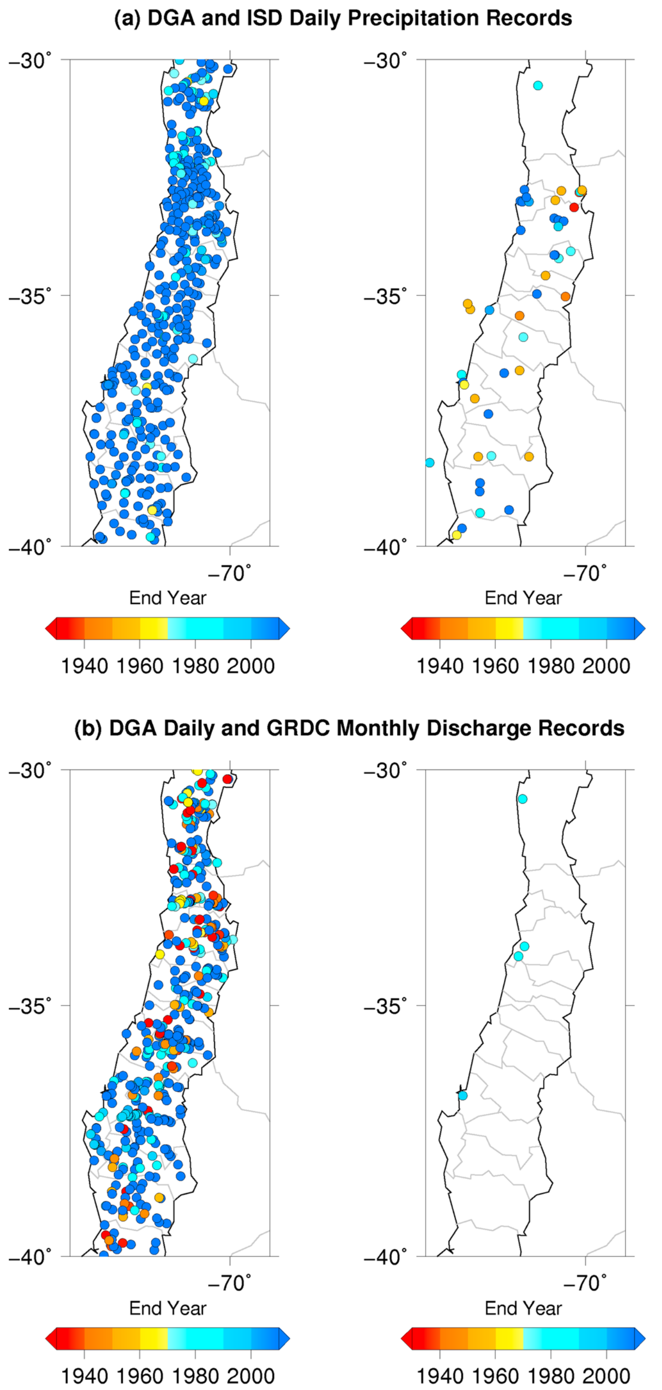

Figure 2. Comparison of station density and record end year for the Dirección General de Aguas (DGA; national water regulatory body) of central Chile and global databases for (a) precipitation stations (DGA versus Integrated Surface Database, ISD); (b) streamflow stations (DGA versus Global Runoff Data Centre, GRDC).

and management cannot be evaluated. Less developed regions tend to have less dense in situ measurement networks that do not provide adequate coverage of even the most essential variables such as precipitation, and this can be a barrier to successful water management. Figure 1 shows the distribution of precipitation and streamflow gauges in the LAC region that are currently available from global data centers that accumulate subsets of national databases, and highlights regions with very few gauges, particularly for streamflow. Some of these gauges are reporting in real time via national or global teleconnection networks, most are not; and many only have data up to several years to decades ago, making it difficult to accurately quantify water resources and extreme event risk. Figure 2 shows the available data record for central Chile, indicating that national networks may have dense historical gauge networks, relative to what is available in global data centers, but often with many caveats to their use for WRM (older stations, not reporting in real time, data in paper form, accumulated values, difficult to access and use).

Table 2 summarizes the variables required for WRM, and their various sources (in situ, RS, models). We also include the characteristics of typical networks and how this enables or constrains different WRM activities. Of key importance is the temporal availability of data: either long-term time series for risk assessment, design and planning, or real-time data for operations and early warning of hazards. Often in situ data are inaccessible for logistical, political, or security reasons, or not available in real time. In particular, there has been a dramatic decline in networks since the 1980s for various reasons; RS data can overcome many of these issues including transcending transboundary disputes on data sharing (Biancamaria et al., 2011; Voss et al., 2013). At the same time, there are trade-offs to using RS data that we highlight here and discuss in detail in subsequent sections. Some variables cannot be retrieved from satellites as yet, and model-based sources of data are sometimes the only source of information, in some regions and at large scales (e.g., wind speed), or can complement in situ and RS sources of data. In section 5 we discuss how models are useful for providing consistent and continuous data records and are the only way of providing physically based hydrological forecasts.

3. Current Remote Sensing Technologies and Products

Satellite remote sensing often represents a critical source of information in regions with limited networks and where information on hydrologic conditions is not accessible (e.g., see case studies in section 3.8). Retrievals are available for most components of the water cycle, limited elements of water quality (e.g., turbidity, chlorophyll and other phytoplankton pigments, dissolved organic content, temperature, and salinity), and the distributions and health of vegetation. Nevertheless, many challenges and caveats to its utility for WRM exist. These include issues related to the quality of the data (how well it represents observed data), resolution (both temporal and spatial, which are very high for some variables and sensors, but suboptimal or not useful for others), sampling (how often and where the sensor samples the land surface), legacy (the length and continuity of long-term records), and latency (how readily available are data in near real time). Many of these challenges are related to the design of sensors and their orbital characteristics, which in many cases were not designed with water variables and water management in mind, or are indirect measurements that require often substantial processing and retrieval models to derive the required variable. The reliance on a retrieval model has implications for how these types of data are used as *observations*, more so when other modeled

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Table 2
Relevant Variables for WRM From In Situ Networks, RS, and Models, Including Spatial and Temporal Availability

Variable	Source	Spatial coverage	Temporal coverage	Utility for WRM
Precipitation	Gauge networks	National gauge networks	Years to decades; Usually limited coverage in real time	Essential, but often limited by availability in real-time or spatial coverage
	RS	Extrapolar regions to global	10–15 years for subdaily data; near real time	Essential in regions with sparse in-situ networks, but products are subject to large uncertainties and may have short time series.
	Models	Regional to global	Variable; near real time	Global and decadal coverage but large uncertainties
ET, PET	Gauge networks (pan PET)	National networks	Years to decades	Essential for evaluating crop water demands
	Flux towers (ET)	Limited points	1–10 years	Limited number globally, and limited spatial representativeness; Useful for validation
	RS (ET, PET)	Regional to global	Decades; near real time	Global and decadal coverage but large uncertainties
	Models (ET, PET)	Regional to global	Decades; near real time	Global and decadal coverage but large uncertainties. Need a priori knowledge of water management practice
Streamflow	Gauge networks	National networks	Decades; near real time	Essential, but issues of availability in many regions
	RS	Limited to large rivers	Years to decades; limited availability in real time	Large uncertainties and limited coverage, but essential where available
	Models	Regional to global	Decades; in near real time	Only source in unmonitored regions; Large uncertainties, with management effects poorly represented
Water levels	Gauges	Specific water bodies	Years to decades; limited availability in real time	Essential, but issues of availability in many regions
	RS	Limited to large rivers and water bodies	Years to decades; in real time	Limited coverage but useful for specific water bodies
	Models		Decades; in near real time	Large uncertainties but only data source in many regions
Soil moisture	In-situ networks	Limited spatial coverage	Years; limited availability in real time	Useful for local applications; Essential for validation
	RS	Global	Years to decades; available in near real time	Limited depth; but useful if combined with models
	Models	Global	Decades; available in near real time	Large uncertainties but useful for drought applications
Snow and Ice	Gauge networks	Regional	Years to decades; some regional networks available in near real time	Essential where networks are dense
	RS	Global	Years to decades; available in near real time	Essential, but large uncertainties for SWE, more accurate for snow covered area.
	Models	Global	Decades; available in near real time	Large uncertainties, but can complement in-situ and RS
Groundwater	Well networks	Regional		Essential, but limited coverage; Essential for validation
	RS	Global from gravimetry, but coarse resolution	Years; coarse resolution	Measures only total water storage—GW must be interpreted or modeled. Coarse resolution prevents direct use, but has research applications and useful when combined with models
	Models	Regional to global	Years to decades; sometimes available in near real time	Large uncertainties, but useful for regional applications
Water quality	Point sample networks	Limited spatial coverage	Years; limited availability in real time	Essential but limited coverage
	RS	Global	Years; available in near real time	Limited variables surface water only, and large uncertainties depending on the variable
	Models	Dependent on variable	Years to decades; available in near real time	Large uncertainties depending on the variable

Note. WRM = water resources management; RS = remote sensing; SWE = snow water equivalence.

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data (e.g., reanalysis climate data) are required to support the retrievals. A review of the uncertainties associated to RS estimates of hydrologic variables and their applications can be found in Demaria and Serrat-Capdevila (2016).

Satellite remote sensing of relevant variables for water management and hydrological hazard monitoring have evolved considerably from the few early dedicated missions that were focused on snow extent and land cover, to the current routine monitoring of nearly all components of the water balance and vegetation health. This is despite the lack of dedicated missions for many relevant variables and coordination among missions to leverage complementary information. Here we systematically review the state-of-the-art for relevant variables, current satellite missions, and products. We do not focus on water quality variables in this review but note that there is considerable potential for water quality applications that should be reviewed elsewhere. Table 3 provides a summary of selected current missions and products that are useful for WRM (relevant upcoming and planned missions are discussed in section 4). In addition, there are many regional products that provide some of these variables but are not described here. For example, the EUMETSAT Satellite Application Facility on Land Surface Analysis provides a variety of products (MW, IR, and MW-IR merged precipitation; MW-based soil moisture; VIS/IR-based snow cover extent; and MW-based SWE) for Europe that are specifically aimed at operational hydrology and WRM (EUMETSAT, 2018).

3.1. Precipitation

Precipitation is the main driver of the land surface hydrological cycle. It is therefore an essential retrieved variable for a range of applications related to WRM and flood/drought monitoring and early warning. Current operational products include single sensor and multisatellite products, as well as various merged and gauge-calibrated products. These generally rely on combined microwave radiometers and high-resolution radars that provide a physical measurement of rainfall. To overcome the low temporal sampling (once per day or less) of microwave sensors on low Earth orbits, these retrievals are sometimes merged with infrared retrievals (that provide an indirect measure) from geostationary satellites to essentially interpolate between microwave overpasses. Current operational products include the Tropical Rainfall Measurement Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA; 0.25°, 3-hourly; Huffman et al., 2007), which is based on thermal infrared (TIR)-estimated rainfall calibrated with precipitation radar and merged with the TRMM microwave imager (TMI) and other passive microwave data (e.g., SSM/I) as available; PERSIANN (0.25°, 1-hourly; Hsu et al., 1997) is based on TIR and uses passive microwave (TMI, SSM/I, and AMSU) to train a neural network to estimate rain rates; CMOPRH (0.07°, 30 min; Joyce et al., 2004), which combines passive microwave retrievals such as TMI, SSM/I, AMSU, and AMSR-E and uses TIR to translate between microwave retrievals; and GSMAP (0.1°, hourly; Aonashi et al., 2009), which combines passive microwave, including TMI, SSM/I, and AMSU.

The Global Precipitation Measurement mission (GPM; Smith et al., 2004) and its IMERG product is currently the most promising source of precipitation data given its next generation observations of rain and snow worldwide every 3 hr at 10-km resolution. The core satellite was launched in February, 2014, which carries the GPM Microwave Imager that captures precipitation intensities and horizontal patterns and the Dual-frequency Precipitation Radar that provides insights into the three-dimensional structure of precipitating particles. The GPM extends the capabilities of the TRMM sensors to measure light rain and quantify microphysical properties of precipitation. It therefore has obvious applications for drought monitoring globally, plus flood risk and water availability.

Other products such as CHIRPS (Funk et al., 2015) and MSWEP (Beck et al., 2016) combine available satellite products with gauge data. MSWEP optimally merges gauge observations (GHCN-D, GSOD, and others), remote sensing data (CMORPH, GridSat, GSMaP, and TMPA 3B42RT), and model outputs (ERA-Interim, JRA-55, and NCEP-CFSR). CHIRPS (0.05°, daily) combines the long-term climatologies of TRMM and CMORPH with TIR cloud cover data and merges with gauge data where available. Although GPM and similar combined products have made advances, they still fall short in representing the high spatial and temporal variation and intermittency of precipitation. Statistical downscaling methods (e.g., He et al., 2016) that relate the current quasi-global precipitation products and high-resolution predictors may currently be the only feasible way to produce higher resolution (below 1 km) over large scales.

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Table 3
Summary of Selected Current Satellite Missions and Satellite-Based Products That Are Useful for WRM, Flood, and Drought Monitoring

Mission	Launch date/product start and extent	Spatial resolution	Temporal resolution	Notes
Precipitation				
TMPA	2000–2018	0.25°60°S to 60°N	3 hr	Huffman et al. (2007). Based on TIR-estimated rainfall calibrated with precipitation radar and merged with the TMI and other passive microwave data. Replaced by IMERG (see below). https://pmm.nasa.gov/data-access/downloads/trmm
PERSIANN	2000 to present	0.25°60°S to 60°N	1 hr	Hsu et al. (1997). Combines TIR and passive microwave (TMI, SSM/I, and AMSU). Available 2 days from real-time. http://chrsdata.eng.uci.edu
CMORPH	2002 to present	0.07°60°S to 60°N	30 min	Joyce et al. (2004). Combines passive microwave retrievals such as TMI, SSM/I, AMSU, and AMSR-E and uses TIR to translate between microwave retrievals. http://www.cpc.ncep.noaa.gov/products/janowiak/cmorph_description.html
GSMAP	2005 to present	0.1° global	1 hr	Aonashi et al. (2009). Combines passive microwave, including TMI, SSM/I, and AMSU. http://sharaku.eorc.jaxa.jp/GSMaP_crest/
GPM/IMERG	2015 to present	0.1°60°S to 60°N	30-min	Constellation of satellites provides quasi-global, subdaily, near-real-time coverage. Up to 6-hr from real time. https://pmm.nasa.gov/data-access/downloads/gpm
CHIRPS	1979 to present	0.05°	daily	Funk et al. (2015). Combines the long-term climatologies of TRMM and CMORPH with TIR cloud cover data, and merges with gauge data where available. http://chg.geog.ucsb.edu/data/chirps/
MSWEP	1979 to present	0.1°	3-hour	Beck et al. (2016, 2017). Optimally merges gauge observations, remote sensing data, and model outputs. http://www.gloh2o.org
Land Surface Temperature (for ET)				
Landsat	2013 (Landsat-8), 2022 (Landsat-9)	30 (multispectral) to100 m (thermal)	16 days	Hosts the Operational Land Imager (OLI) and the Thermal InfraRed Sensor (TIRS). Landsat TIR record goes back to Landsat 4, launched in 1982. https://landsat.usgs.gov
AVHRR	NOAA_19 launched 2009 and MetOp-B launched 2012	1 km	1 day	Full record goes back to 1979. AVHRR-derived products also include land cover and LAI. https://lta.cr.usgs.gov/AVHRR
ASTER	2000	90 m	16 days	NASA et al. (2001). Based on five TIR bands. https://asterweb.jpl.nasa.gov/data.asp
MODIS	2000	1 km/6 km	1 day, 8 day	Various different resolution products available globally. https://modis.gsfc.nasa.gov/data/dataprod/mod11.php
VIIRS	2011	375–750 m	1 day	Follow-on from AVHRR and MODIS. https://earthdata.nasa.gov/earth-observation-data/near-real-time/download-nrt-data/viirs-nrt
Sentinel-3	2015/2017	1 km	$<$2 days	Two satellites provide $<$2 days repeat. https://sentinel.esa.int/web/sentinel/sentinel-data-access
ECOSTRESS	2018, 1 year expected	38 $\times$ 69 m	4-day on average, subdaily in focus regions	Hulley et al. (2017). Hosted on the ISS. Core products include Evaporative Stress Index (ESI)
ET products				
RS-PM	1983–2010	0.5°	Daily	Vinokullo et al. (2011). Uses P-M model with environmental constraints based on vegetation indices and near-surface meteorology. http://hydrology.princeton.edu/data.php
MOD16 ET	2000–2014	1 km	8-day	Mu et al. (2011). Uses P-M model with environmental constraints based on vegetation indices and near-surface meteorology. http://www.ntsg.umt.edu/project/modis/mod16.php

Table 3 *(continued)*

Mission	Launch date/product start and extent	Spatial resolution	Temporal resolution	Notes
PT-JPL	1984–2006	1–0°	Monthly	Fisher et al. (2008). Uses a Priestley-Taylor model with environmental constraints based on vegetation indices and meteorology. http://www.landflux.org/Data.php
GLEAM	1980–2016, 2003–2015, 2011–2015	0.25°	Daily	Martens et al. (2017). Uses a Priestley-Taylor model with environmental constraints based on satellite soil moisture and vegetation optical depth. https://www.gleam.eu
SSEBop	2003 to present	1 km	10 days	Senay et al. (2013). Based on the Simplified Surface Energy Balance (SSEB) approach. Combines ET fractions generated from remotely sensed MODIS thermal imagery, acquired every 8 days, with reference ET using a thermal index approach. https://earlywarning.usgs.gov/fews
ALEXI-DisALEXI	Various regional data sets	30 m (Landsat), 1 km (MODIS)	Hourly/daily	Anderson et al. (2007). Disaggregated ET data from the Atmosphere-Land Exchange Inverse Model (ALEXI), a TIR-based surface energy balance model.
Global ESI	2001 to present	0.05°	4- and 12-week composites updated weekly	Anderson et al. (2011). Evaporative Stress Index (ESI) based on MODIS LST and ALEXI ET model. https://servirglobal.net/Global/Evaporative-Stress-Index
Soil moisture				
AMSR-E	2002–2011	25 km	1-day revisit	Njoku (2004). Soil moisture in the top ~1 cm of soil. https://nsidc.org/data/ae_land3
AMSR2	2012	25 km	1-day revisit	Two products: JAXA (Koike, 2013) and NASA-VUA LPRM (Owe et al., 2008). Both provide surface soil moisture. http://nsidc.org/data/au_land
SMOS	2010	15, 25, 50 km	1- to 3-day revisit; daily, 9-day and monthly products	Kerr et al. (2012). Various products available, some in near real time. https://earth.esa.int/web/guest/-/level-2-soil-moisture-6900
SMAP SMAP L4 root zone soil moisture	2015 2015	36 km 9 km	1- to 3-day revisit 3 hr	Entekhabi et al. (2010). Retrievals are for the top few centimeters of the soil. A level 4 product for root zone soil moisture is available based on assimilation into a land surface model (Reichle et al., 2016). https://smap.jpl.nasa.gov/data/
Sentinel-1	2014/2016	< 1 km^2	8 days	Constellation of two polar-orbiting satellites, using C-band synthetic aperture radar imaging, with two more to be launched. Can provide surface water extent and freeze/thaw state in addition to soil moisture. https://sentinel.esa.int/web/sentinel/sentinel-data-access
Surface water height and extent				
Jason-2/3 (surface water height)	2008/2016	Lakes $>$100 km^2	10 days	Lambin et al. (2010). Jason-3 provides continuity from Jason-2. Various near real time (7 day lag) and research quality products are available. For example, G-REALM product include data for 282 lakes and reservoirs globally. https://ipad.fas.usda.gov/cropexplorer/global_reservoir/
Sentinel-3 (surface water height)	2016	350 m along track	27 days	ESA (2012a). Provides data continuity for the ERS, Envisat, and SPOT missions. https://sentinel.esa.int/web/sentinel/sentinel-data-access
Landsat (surface water extent)	2013 (Landsat-8), 2022 (Landsat-9)	30 (multispectral) to 100 m (thermal)	16 days	Surface water extent can be retrieved using indices such as NDWI. https://landsat.usgs.gov
MODIS (surface water extent)	2000 to present	500 m	Daily	Surface water extent from NDWI. For example, NASA MODIS Near Real Time Global Flood Mapping Project (https://floodmap.gsfc.nasa.gov).
Sentinel-2 (surface water extent)	2015/2017	10–60 m	5/10 days	Surface water extent from NDWI. 5 day repeat from two satellites. https://sentinel.esa.int/web/sentinel/sentinel-data-access

Table 3 *(continued)*

Mission	Launch date/product start and extent	Spatial resolution	Temporal resolution	Notes
Snow				
MODIS SCE	2000 to present	500 m 0.05°	Daily and 8-day composite	Hall and Riggs (2016a, 2016ab). Various resolution products available. https://nsidc.org/data/modisx
VIIRS SCE	2012 to present	375 m (swath),500 m	Daily and 8-day composite	Key et al. (2013). Provides continuity from MODIS Terra and Aqua version 6 snow cover. https://nsidc.org/data/viirs
AMSR-E SWE	2000–2011	25 km	Daily, 5-daily, monthly	Tedesco et al. (2004). Errors can be large due to land heterogeneities such as variable snow crystal sizes, snow detection in mountainous terrain, wet snow discrimination and mapping snow in densely-forested areas. http://nsidc.org/data/ae_dysno
Groundwater				
GRACE	2002	500,000 km^2	30 days	Tapley et al. (2004). Measures total water storage change. Separation of individual components such as groundwater, soil moisture and snow requires interpretation through modeling. https://grace.jpl.nasa.gov/data/get-data/
GRACE FO	2017	500,000 km^2	30 days	Flechtner et al. (2016). Follow on mission to extend GRACE record
Vegetation				
Landsat	2013 (Landsat-8), 2022 (Landsat-9)	15 m	16 days	Various vegetation indices can be calculated including NDVI.https://landsat.usgs.gov
AVHRR/GIMMS	1979–2015	1 km	7-/14-day composites	The latest version of the GIMMS NDVI data is NDVI3g.v1. https://nex.nasa.gov/nex/projects/1349/
MODIS	2000	250 m, 1 km, 0.05°	16-day, monthly	NDVI and Enhanced Vegetation Index (EVI) plus reflectances centered on individual bands.
VIIRS	2012	375 m (swath), 500 m	Daily and 8-day composite	Vargas et al. (2013). Provides continuity from MODIS. https://modis.gsfc.nasa.gov/data/dataprod/mod13.php
SPOT/PROBA-V	1990–2017	1 km	10-day	NDVI, Vegetation Condition Index (VCI), LAI. http://hyperforest.vgt.vito.be/content/products
Sentinel-2	2015/2017	10–60 m	5/10 days	5-day repeat from two satellites. https://sentinel.esa.int/web/sentinel/sentinel-data-access

Note. VIIRS = Visible Infrared Imaging Radiometer Suite; AVHRR = Advanced Very High Resolution Radiometer; GRACE = Gravity Recovery and Climate Experiment; GRACE FO = GRACE Follow-On; SWE = snow water equivalence; MODIS = Moderate Resolution Imaging Spectroradiometer; SMAP = Soil Moisture Active Passive; SMOS = Soil Moisture and Ocean Salinity; ECOSTRESS = ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station; TMPA = Tropical Rainfall Measurement Mission Multi-Satellite Precipitation Analysis.

Figure 3 demonstrates the complementary strengths of reanalyses such as ERA-Interim and satellite data sets such as CMORPH V1.0, TMPA 3B42RT V7, and PERSIANN-CCS: reanalyses exhibit substantially better performance in regions dominated by predictable large-scale stratiform systems (e.g., Chile), while remote sensing yields much better performance in regions dominated by less predictable intense, localized convective systems (e.g., the Amazon). The good performance exhibited by the satellite- and reanalysis-based MSWEP-ng V2.0 product shows that careful data merging can exploit these complementary strengths.

3.2. ET (and LST)

ET provides the link among the water energy and carbon cycles, making it the linchpin variable of the coupled earth system. As ET cannot be measured directly from space, and is dependent on a range of environmental (near-surface meteorology and radiation) and biophysical controls (e.g., soil moisture, plant phenology, and vegetation characteristics) factors, ET retrievals require a range of inputs from multiple sensors, and often supporting data from ground observations and models. Algorithms are generally based on satellite land surface temperature (LST) measurements (Kalma et al., 2008; Kustas et al., 1995; Su, 2002).

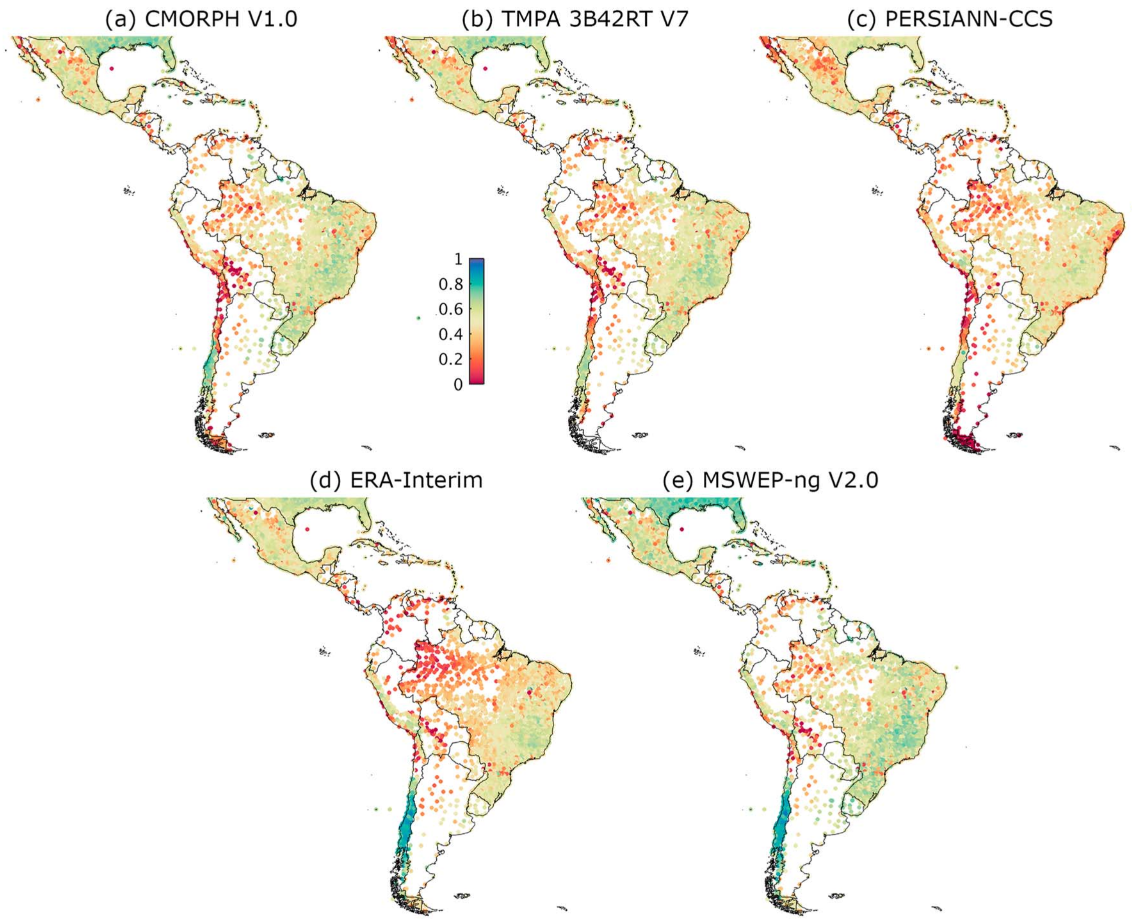

Figure 3. For a selection of non-gauge-corrected *P* data sets, Pearson correlations calculated between 3-day mean gauge- and data set-based *P* time series. Each data point represents a gauge. We only considered data during 2000–2016. The gauge observations were compiled from the Global Historical Climatology Network-Daily database (Menne et al., 2012), the Global Summary of the Day database (https://data.noaa.gov), the Latin American Climate Assessment and Dataset database (http://lacad.ciifen-int.org), the Chile Climate Data Library (http://www.climatedatalibrary.cl), and national databases for Mexico, Brazil, and Peru. Figure adapted from Beck et al. (2017). P data sets are (a) CMORPH V1.0, (b) TMPA 3B42RT V7, (c) PERSIANN-CCS, (d) ERA-Interim, (e) MSWEP-ng V2.0.

When combined with air temperature data, one can estimate the surface sensible heat flux and back out latent heat (and therefore ET) with additional data on net radiation. The Landsat sensor-based TIR retrievals are the current state-of-the-art, with retrievals at the resolution of 100 m, but limited by cloud cover and temporal sampling of only every 16 days (Anderson, Allen, et al., 2012). Other products include the coarser but more frequent retrievals based on the long-term Advanced Very High Resolution Radiometer (AVHRR) series of sensors (1.1 km; since 1978) and Moderate Resolution Imaging Spectroradiometer (MODIS; 1 km since 2000), and geostationary satellites with resolutions of about 4–5 km. Combining sensors can be used to overcome the temporal and spatial sampling limitations of individual sensors (e.g., Gao et al., 2010).

The recently launched (mid-2018) National Aeronautics and Space Administration (NASA) ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station sensor focuses on vegetation temperature measurement to understand how plants use water and respond to stress. Of interest here, the sensor can be used for monitoring of agriculture and in particular the consumptive use of water. The sensor is a multispectral TIR radiometer that measures surface temperature and is hosted on the International Space Station (ISS). It improves on existing high-resolution, but low repeat data (e.g., Landsat), and high repeat but low resolution (e.g., MODIS) sensors by providing an average 4-day repeat cycle over the ISS coverage area and up to several retrievals per day in some times and places, and a spatial resolution 38 × 57 m, which allows mapping of ET variability within fields. Core products include the Evaporative Stress Index that provides an indication of drought conditions. The mission is focused on the continental United States and selected important biomes around the world, including European and South Asian agricultural zones, with a nominal lifetime of 1 year.

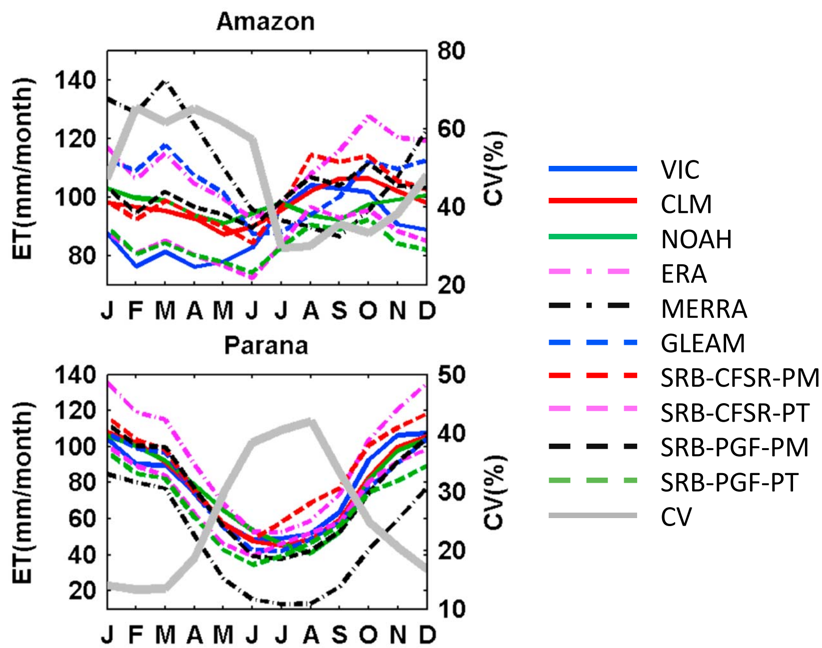

Figure 4. Seasonal cycle of evapotranspiration from different products over two large South American river basins for 1984–2007, plus the coefficient of variation (CV) across products. GLEAM (Global Land Evaporation Amsterdam Model; Martens et al., 2017) is a remote sensing-based product that constrains PET calculated with the Priestley-Taylor (PT) method, by satellite soil moisture and vegetation optical depth. The different surface radiation budget (SRB) products are based on the PM or PT methods using net radiation from the SRB data set (Stackhouse et al., 2011), and PGF or CFSR (Climate Forecast System Reanalysis; Saha et al., 2010) reanalysis meteorological data. The RS ET products are compared with estimates from land surface models and reanalyses. VIC (Variable Infiltration Capacity; Liang et al., 1994), CLM (Community Land Model; Lawrence et al., 2011), and NOAH (Noah; Ek et al., 2003) are three land surface models forced by the Princeton Global Forcings (PGF, Sheffield et al., 2006; http://hydrology.princeton.edu/data.php). ERA (ERA-Interim; Dee et al., 2011) and MERRA (Modern-Era Retrospective analysis for Research and Applications; Rienecker et al., 2011) are reanalysis data sets. Figure adapted from Zhang, Pan, et al. (2017).

The inability of TIR-based approaches to make retrievals under cloud cover has led to a diversity of gap-filling approaches and alternative approaches, although not necessarily with the spatial detail provided by TIR data. For example, there have been efforts to integrate coarse resolution LST data from microwave Ka-band sensors to gap-fill persistently cloudy regions (Holmes et al., 2018). Alternatively, the physically based Penman-Monteith (PM) algorithm has also been used to gap fill and is used as an approach in its own right to overcome TIR limitations. The PM approach scales potential evaporation (PET) estimated from meteorological data by estimated environmental constraints such as soil moisture and plant stomatal closure (Jarvis, 1976). For example, there are several global products that use variants of the PM algorithm and use mostly satellite based data to retrieve ET at daily and tens of kilometers scales, such as the MODIS-based algorithm of Mu et al. (2011) and the multisatellite approach of Vinokullo et al. (2011). The way in which the environmental constraints are estimated has a large influence on estimated ET, and therefore large differences among products (Vinokullo et al., 2011). The reliance on estimates of PET in turn relies on near-surface meteorological data and surface radiation, which can variously be sourced from remote sensing, reanalysis, and gridded analyses of station data and thus are subject to the errors in these different approaches (e.g., Ferguson et al., 2010). Figure 4 compares different remote sensing based products with reanalysis and land surface modeling for the Amazon and Parana River basins and shows large uncertainties, especially in the representation of seasonality of ET over the Amazon. Part of this uncertainty may be due how satellite retrieval and land surface models represent subsurface water that can maintain ET during the dry season (Guan et al., 2015), and the uncertainty in quantifying the interception component of ET, which is likely of the order of 15% of total precipitation in tropical regions and up to 30% in needleleaf forests (Miralles et al., 2010).

Current challenges to retrieving ET at resolutions relevant for flood/drought risk management include how to develop higher-resolution retrievals with daily or subdaily frequency (Norman et al., 2003). This can only be

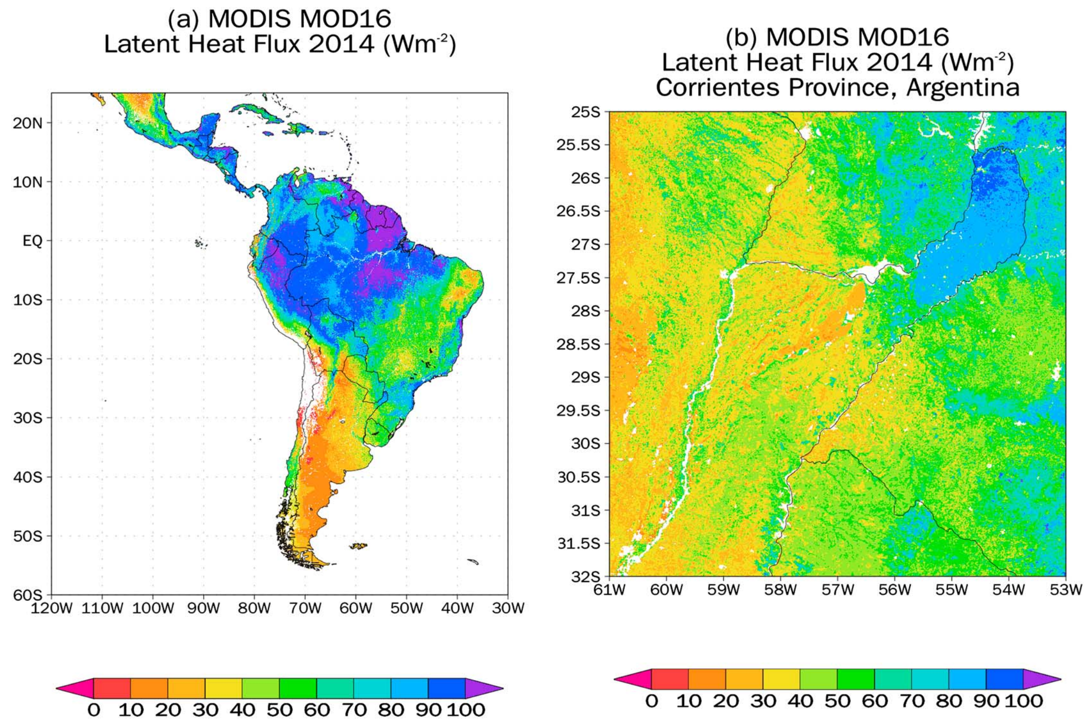

Figure 5. Mean annual latent heat flux for 2014 at 1-km resolution, from the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD16 product for (a) Latin America and the Caribbean and (b) focused on the Corrientes province in northeast Argentina. Regions of land in white are either water bodies, barren ground, permanent snow/ice, permanent wetland or urban.

done by combining sensors from constellations of polar orbiting satellites (e.g., Landsat and MODIS as with the approach of Cammalleri et al., 2013) or using different sensors on geostationary satellites, although there are no planned dedicated missions. There are also considerable uncertainties in the ancillary data for surface radiation, and supporting parameters such as albedo and surface emissivity, although new geostationary satellite-derived products show large improvements over model-derived products, with subsequent improvements in ET retrievals (Urraca et al., 2017). Further challenges remain because of large differences between algorithms and against in situ observations, such as from flux towers (Ershadi et al., 2014; Michel et al., 2016; Miralles et al., 2016). Figure 5 shows an example of a relatively high-resolution (1 km) ET retrieval from the MODIS MOD16 product for the LAC region overall, and for northeast Argentina, highlighting the variations between natural forest land cover to the northeast, unirrigated agricultural lands, and rangelands elsewhere.

3.3. Soil Moisture

Soil moisture is extremely useful in drought applications, particularly for agriculture, and also enables identification of flood inundation, or wet antecedent conditions that favor subsequent flooding. However, soil moisture is highly variable in time and space, being driven by a range of factors that act at different scales, such as topography, soil properties, vegetation, and climate drivers (Crow et al., 2012), which can only be sampled from space, given the dearth of dense in situ measurements. Soil moisture measurements from space have until recently been opportunistic, drawing from the suite of microwave sensors that have flown since the late 1970s. Retrievals are based on the fact that changes in surface soil moisture are associated with changes in surface emissivity and the backscattering properties in microwave frequencies and can therefore be measured using microwave radiometers and radars, respectively. Retrievals are, however, limited by the penetration depth of the microwave radar signal and the emission depth to the top centimeter or so of the soil and are heavily attenuated by dense vegetation and heavy precipitation, limiting retrievals to bare ground and sparsely vegetated regions. Penetration depth increases with longer wavelengths but are still limited to about 5 cm at most with 1.5-GHz L-band frequencies because of satellite antenna design limitations.

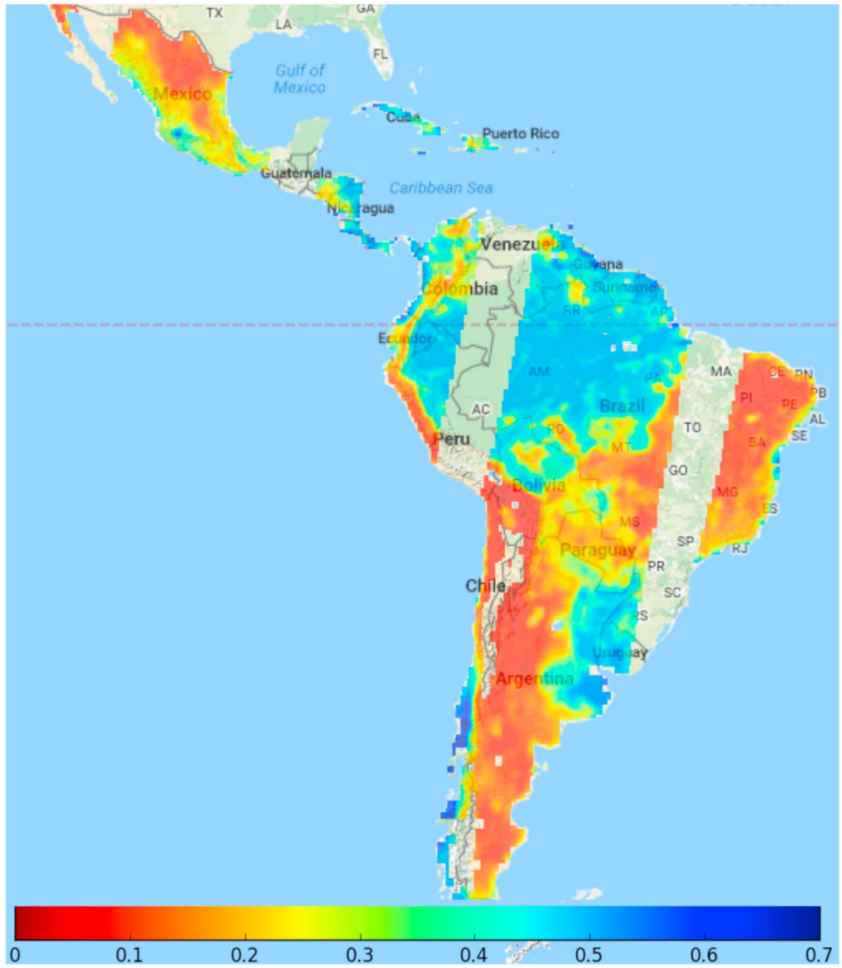

Figure 6. SMAP 3-day composited volumetric soil moisture (m^3/m^3) over the LAC region, from the Latin America and Caribbean Flood and Drought Monitor (LACFDM, 2017). The tracks of missing data are due to the orbit of the SMAP satellite, which repeats swath coverage once every 8 days.

The first dedicated soil moisture mission was the European Soil Moisture and Ocean Salinity (SMOS) mission that was launched in 2009 (Kerr et al., 2012) and was followed by the NASA Soil Moisture Active Passive (SMAP) mission launched in January 2015 (Entekhabi et al., 2010). SMAP was designed for global mapping of soil moisture at a 10-km spatial resolution with a 2- to 3-day revisit time under both clear and cloudy sky conditions (see Figure 6). This improves on the resolution relative to AMSR-E (25 km) and SMOS (50 km) by combining an L-band radar (high resolution 1–3 km, lower accuracy) and an L-band radiometer (low resolution 40 km, higher accuracy), as well as retrievals for a wider range of vegetation conditions and for the top 5 cm of the soil. SMAP products also include level 4 (L4) root zone estimates by merging SMAP observations with land surface model estimates via assimilation extending the utility of the data (Lievens et al., 2017). Unfortunately, the SMAP radar failed in July 2015 thus restricting soil moisture products to the 40-km resolution of the radiometer.

The various retrievals have been merged into long-term climate data records that provide consistent data sets for analysis of long-term changes and a stable climatology for calculating drought and flood indices. These have global coverage for the past approximately 30 years, including the National Oceanic and Atmospheric Administration (NOAA) NESDIS Soil Moisture Operational Products System (Liu et al., 2016) and the European Space Agency (ESA) Soil Moisture Essential Climate Variable (Liu et al., 2012). These blend various combinations of SMMR, TMI, SSM/I, AMSR-E, WindSat, SMOS, SCAT, ASCAT, and SMAP sensors (Lettenmaier et al., 2015). Although, there has been great strides in the development of algorithms and now the availability of data from dedicated sensors, the generally coarse resolution and representation of only the top few centimeters has hampered the use of soil moisture retrievals in hydrological applications beyond regional drought monitoring. It may be that the best current use is for assimilation into models: either process-based (Reichle et al., 2007) or downscaling models (Jha et al., 2013). Future improvements to the resolution and depth may be possible through improvements in antenna technologies, although the prospects for this are unclear. Continued validation and testing is required to improve the accuracy of the retrievals, and the maintenance and use of global networks of in situ measurements of soil moisture is crucial to this (Dorigo et al., 2011).

The recently launched ESA Sentinel-1 satellites are paving the way for the new generation of retrievals that can reach resolutions of 1 km or less (Paloscia et al., 2013). The mission comprises of a constellation of two polar-orbiting satellites, operating day and night using C-band synthetic aperture radar imaging. It is intended to provide continuity of data from ERS and Envisat, but at higher revisit time (3 days over Europe; 8 days globally), and coverage (5×30 m^2). A set of four Sentinel-1 satellites have been launched or are in production. Sentinel-1a was launched in 2014 and the Sentinel-1b in 2016. Being a synthetic aperture radar (SAR) sensor, there is potential to retrieve several hydrological parameters in addition to soil moisture, including surface water extent (section 3.4) and freeze/thaw state.

3.4. Surface Water Height and Extent

The observation of surface water from space is of importance for mitigating the impacts of hydrological extremes because of the role of surface water bodies and rivers in providing storage during periods of drought, and as the conveyance of flood waters. This applies to man-made reservoirs also, which can serve multiple purposes such as water storage and flood control. Flooding also manifests as temporary surface water that can be observed from space. In all cases, the goal is to measure the height and extent of the surface water and potentially derive the volume based on local bathymetric measurements.

Identification of surface water can be achieved either from optical or microwave sensors (passive and radar), although as noted above, optical sensors suffer from cloud contamination that makes them difficult to use for flood detection and mapping, for which the temporal scales are small. Optical approaches use, for example, spectral band differences such as the Normalized Differences Water Index (NDWI; McFeeters, 1996). The NDWI uses the green and NIR bands based on the strong absorption and low radiation of water bodies in these spectral ranges, although it can be subject to misidentification of built-up (urban) areas. Other indices such as the Modified NDWI replace the NIR with the short-wave infrared (SWIR) band (Xu, 2006) with improved accuracy, an approach that has been used to map changes in surface water over the past 32 years from the Landsat archive (Pekel et al., 2016).

In contrast, microwave-based approaches are essentially immune to cloud and rainfall. Radar technologies rely on the low backscattering of water surfaces relative to surrounding land surfaces but return signals can be attenuated by wave action on the water surface. Radiometers detect the lower brightness temperature of the water, but as with soil moisture suffer from low spatial resolution that makes them of less use in observing smaller or complex water bodies and inundation. Active sensors can also be used to measure water levels (Berry et al., 2005; Birkett, 1994), which is useful for monitoring the fluctuations of lakes and reservoirs, although these are generally limited to larger water bodies to achieve acceptable accuracy (Gao et al., 2012).

The Sentinel-2 mission (Drusch et al., 2012) launched in 2015 provides unprecedented information from which surface water fluctuations can be derived. In particular, the revisit time of 10 days for the current satellite (Sentinel-2A) and 5 days when the second satellite was launched in early 2017 will enable monitoring of rapid changes. It monitors across a range of 13 spectral bands from visible and NIR to SWIR at a range of resolutions from 10 to 60 m, and a 290-km field of view, which provides an unprecedented combination of spectral and spatial resolution and coverage. The sensor also has the potential to provide information on water quality and pollution through chlorophyll concentrations, algal blooms, and turbidity (e.g., Gernez et al., 2015).

The derivation of river discharge from satellites is generally based on replicating the approach taken for in situ measurements that uses a rating curve that connects measured river water level (stage) to unmeasured discharge. River stage is measured using radar-based altimeters which are capable of measuring water levels

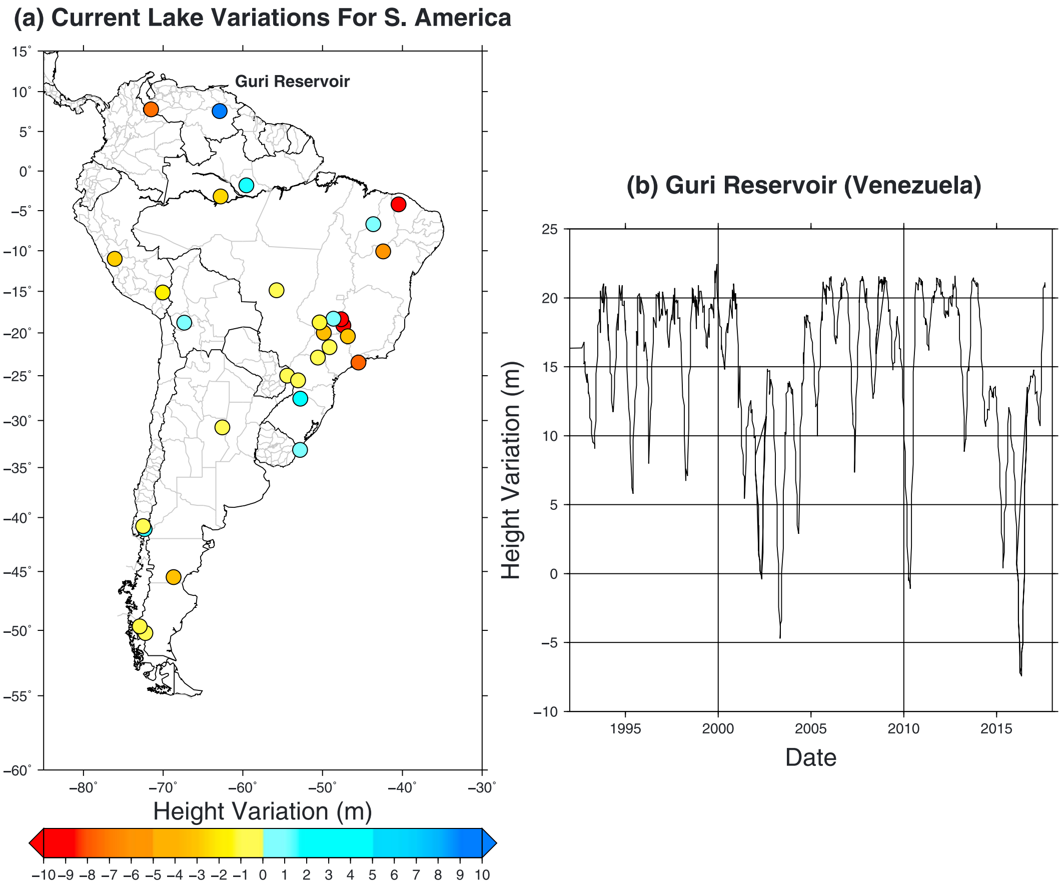

Figure 7. (a) Location of large lakes and reservoirs with altimeter records in the G-REALM database, which is based on the of altimeter record of the U.S. Department of Agriculture's Foreign Agricultural Service/National Aeronautics and Space Administration G-REALM lake level products (U.S. Department of Agriculture's Foreign Agricultural Service/National Aeronautics and Space Administration, 2017). Colors indicate lake height variations for the most recent retrievals (approximately the past 1–2 months depending on the lake) and relative to a datum for a single satellite overpass particular to the lake. (b) Height variations for Guri Reservoir in Venezuela based on various satellite missions, including Jason-3 for the most recent part of the record.

at sufficient accuracy. However, they are limited by the lack of velocity measurements to develop rating curves for arbitrary river reaches. Furthermore, state-of-the-art altimeters that were originally designed for measuring ocean topography have revisit times of only 10 days or more and are limited to large rivers that enable enough radar pulses to be gathered to reduce errors. These missions include the Topex/Poseidon (Fu et al., 1994), Jason-1 and Jason-2 (Lambin et al., 2010), and ENVISAT radar altimeter (Resti et al., 1999), and the newly launched Jason-3 satellite. Figure 7 shows the locations of altimeter records for large lakes and reservoirs across the LAC region, which for the most recent period are based on the Jason-3 sensor. The figure also shows an example time series of lake variations for the Guri Reservoir in Venezuela showing the seasonality of the reservoir and also the large drought periods, most recently in 2016, which curtailed water supply and electricity production in the region. The upcoming Surface Water Ocean Topography (SWOT) mission that is set to launch in 2021 will address many of the issues pertaining to current sensors, in particular the limitation to large rivers and water bodies (see section 4).

3.5. Snow

The importance of snowpack and land ice cannot be understated for many areas of the world (Sturm et al., 2017). The seasonal snowpack is an important water resource that partially supplies one fifth of the world's population (Barnett et al., 2005) and can both contribute to alleviating and exacerbating drought conditions. Rapid snowmelt can also contribute to flooding, and heavy rain on frozen soils can lead to flood conditions that would not otherwise happen. The routine retrieval of snow cover has been carried out for several decades (Hall et al., 1995) drawing from the first photographs taken on weather satellites from the 1960s (Barnes & Bowley, 1968). Long-term records are available (Frei et al., 2012), for example, from the U.S. National Snow and Ice Data Center such as the weekly, 25-km, data set (Brodzik & Armstrong, 2013) that covers the northern hemisphere and goes back to 1966, which draws from interpretation of AVHRR, Geostationary Operational Environmental Satellite (GOES), and other visible-band satellite data (Helfrich et al., 2007). Higher-resolution products are available for the more recent years such as the Interactive Multisensor Snow and Ice Mapping System that is available at daily, 1-km resolution from 1997 (National Ice Center, 2008), although only for the northern hemisphere, and the MODIS-/Terra-based products at daily, 500-m resolution that are available globally from 2000 (Hall & Riggs, 2016a; see Figure 8). These approaches rely on optical sensors that leverage from the high reflectivity in the visible part of the spectrum and also the higher absorption in the SWIR part that allows distinction between snow and thick clouds, which are more reflective. Current challenges include the identification of mixed pixels that include non-snow covered parts, and automated methods for unmixing the spectral signatures to derive the fractional coverage of snow within a pixel (Dozier et al., 2009). Hyperspectral sensors with many hundreds of bands are needed to resolve this challenge and several planned and potential missions could address this, such as NASA's proposed Hyper-spectral Infrared Imager (HyspIRI), the Space Agency of the German Aerospace Center's EnMAP (Environmental Mapping and Analysis Program), and the Italian Space Agency's PRISMA (Hyperspectral PRecursor of the Application Mission; see section 4).

Despite this, the retrieval of the water contained in the snowpack, rather than its areal coverage, is much more important to water resources and flood/drought monitoring and prediction (Mernild et al., 2017; Schneider & Molotch, 2016; Tedesco & Jeyaratnam, 2016). However, the retrieval of snow water content (usually termed as SWE) remains very challenging (Tedesco & Jeyaratnam, 2016) because of the complexities of changes in dialectic properties of snow crystals as they age, the snow accumulation and melt processes that lead to highly variable spatial distributions of snow and meltwater within the snowpack, especially in mountainous regions, and variations in snow consistency in terms of the distribution of snow density and ice layers within the snowpack that may also be contaminated with soot and dust (Molina et al., 2015). The interaction of snow with vegetation also complicates retrievals. Gravimetric approaches such as Gravity Recovery and Climate Experiment (GRACE) detect the seasonality of regional snowpacks but are too coarse to be of practical use. The main approach to retrieving SWE is via microwave technologies, and passive microwave is the most mature. Ice particles and water have quite different scattering and dielectric properties in microwave wavelengths compared to optical wavelengths, and these change with wavelength. The retrieval of SWE is therefore based on the differences in brightness temperature at different wavelengths in the range of 1 to 40 GHz. Retrievals are hampered by the coarse resolution especially relative to the highly heterogeneous nature of snowpack in many regions and the impact of vegetation cover, and the fact that signal become saturated in deep snowpack that limits retrievals to the top 2 m (Josberger & Mognard, 2002).

Blending of information across sensors of different types appears to be the most promising approach (Frei et al., 2012), but such systems have yet to be developed to provide the necessary resolution (perhaps ~100 m in mountainous regions) and temporal repeat (at least weekly). Microwave radar can solve some issues related to resolution and SAR approaches have been proposed that also address issues of sensing wet snow, such as ESA's CoreH2O (ESA, 2012c) and NASA's Snow and Cold Lands Processes, but these have not been selected or have yet to be selected, respectively. Again, merging of information with models may be the best way forward to provide high space and time resolution data on SWE and snow depth, and several experimental and operational systems exist (e.g., NLDAS and SNODAS).

3.6. Groundwater

Groundwater is a crucial resource in many regions of the world, particularly where surface water is scarce, polluted, or shared. In the context of droughts, groundwater is a vital resource that can alleviate surface water drought but can also propagate drought conditions because of the long residence times of even near-surface aquifers. However, groundwater resources are often unsustainable because of low recharge rates, and several areas of the world are hotspots of declining water tables because of human activities, in particular, irrigation (Rodell et al., 2018). As groundwater is below the surface it cannot be directly measured from space, but indirect methods based on either satellite gravimetry or radar interferometry can infer changes in water storage by measuring changes in the earth's gravity field and surface elevation, respectively.

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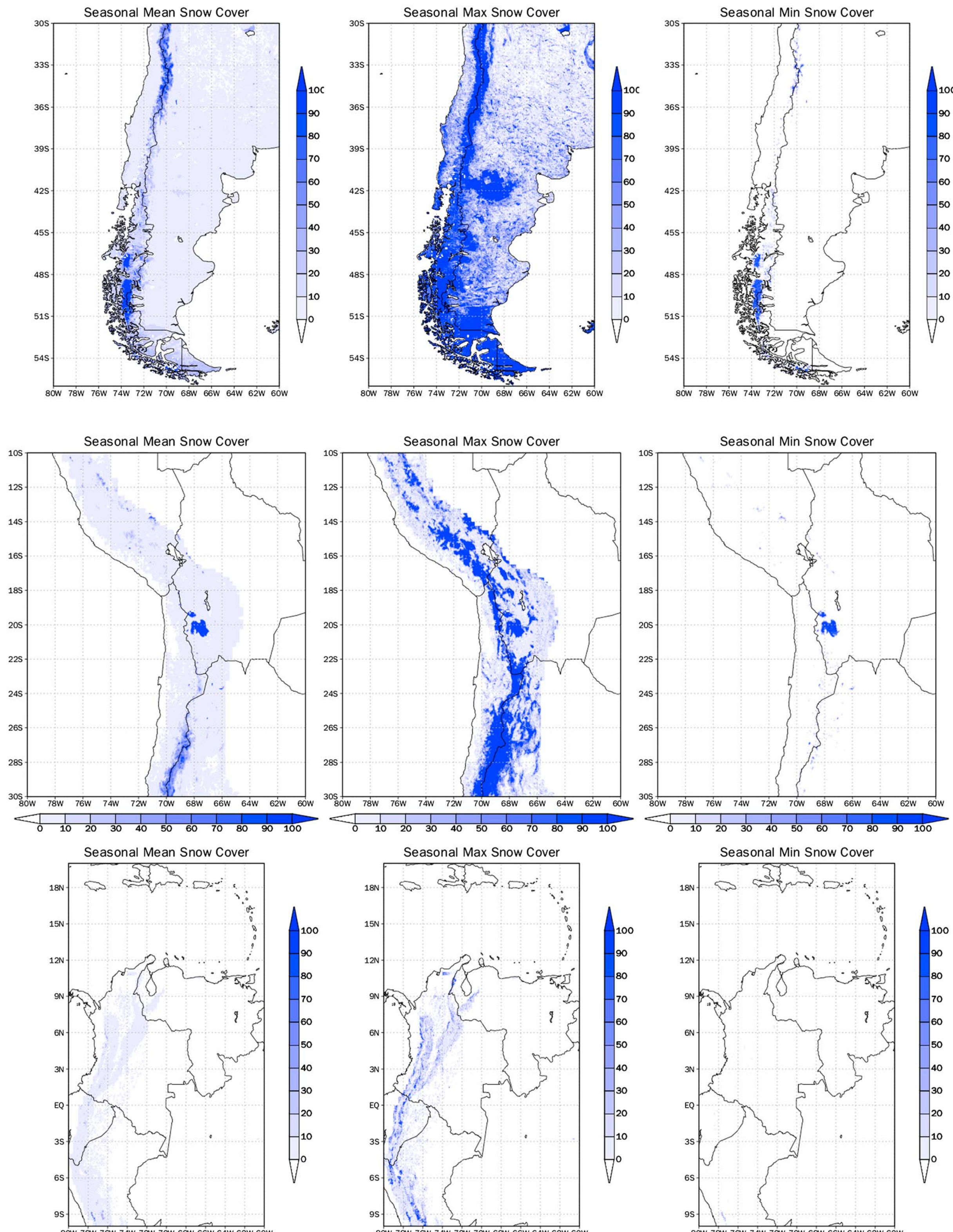

Figure 8. Regional snow cover extent percentage for 2016 for (left column) seasonal mean, (middle column) seasonal maximum, and (right column) seasonal minimum in snow covered area. Regions are (top row) southern South America encompassing central and southern Chile and Argentina, including the southern Andes mountains; (middle row) the central Andes including northern Chile, southern Peru, and Bolivia; and (bottom row) northern Andes through northern Peru, Ecuador, and Venezuela. Data are derived from the Moderate Resolution Imaging Spectroradiometer snow cover extent product (Hall & Riggs, 2016b) and are filtered for cloud cover >30%.

Currently, the GRACE pair of satellites is a dedicated mission launched in 2002 to measure variations in the Earth's gravity field and is used to derive changes in total water storage of which groundwater is a key contributor (along with changes in snowpack and soil moisture; plus lesser contributions from surface water). GRACE is unique among sensors in that it does not rely on electromagnetic radiation emitted or reflected from the Earth's surface and is the only sensor that provides continuous global coverage of storage changes. Despite this, the key drawback of GRACE is the coarse resolution (~500 km) of the retrievals that are limited by the continuous retrievals of gravity fields and its orbit and elevation, and so its use in applications is likely to be limited, unless used in concert with other satellite products or models. For example, there is potential to separate the different components of the GRACE signal using temporal decomposition (Andrew et al., 2017) or modeling (Zaitchik et al., 2008) and use modeling to effectively downscale the coarse GRACE signal (Girotto et al., 2016), and this approach is starting to be used in development applications (e.g., Iqbal et al., 2017). Nevertheless, GRACE has proven outstanding in research contexts in its ability to detect specific changes in water related features such as regional groundwater depletion (Rodell et al., 2009) and large-scale wetland dynamics (Azarderakhsh et al., 2011; Frappart et al., 2015) and has been used successfully to back out large-scale estimates of runoff or ET (Long et al., 2014).

3.7. Vegetation

Remote sensing of vegetation cover and its health status is extremely important for monitoring the impacts of drought, particularly for understanding the status of crops and pastoral areas. Vegetation also acts as a mediator of the hydrological cycle, controlling the majority of ET through transpiration, and contributing to the partitioning of surface energy through the albedo. Of interest is the health of plants (or *greenness*) for understanding ecosystem health and crop productivity under drought conditions. This can be characterized in many different ways including geometric variables such as height, LAI and fractional vegetation coverage, or physiological parameters such as photosynthetic activity or fraction of sunlight absorbed by canopies (fPAR). Products based on these variables can be used to identify and monitor irrigated areas based on contrasting signatures in relation to surrounding areas. Remote sensing is also essential for providing land cover mapping, in particular for distinguishing between managed and unmanaged lands, including croplands and forests. Vegetation properties are best retrieved using visible/infrared (VIR) sensors, although microwave based data such as vegetation optical depth are generally underutilized (Liu et al., 2011). Vegetation optical depth is derived from microwave data, often in concert with soil moisture retrievals (Pan et al., 2014) and provides an approximation of vegetation water content and therefore the hydrological functioning of plants.

There is a long legacy of retrievals based on VIR indices such as LAI and Normalized Difference Vegetation Index (NDVI), although there is an argument that the reliance on narrowband indices is missing opportunities to use multispectral and hyperspectral information from current and proposed missions. Long-term time series of NDVI, LAI, and fPAR exist from a range of satellites including the AVHRR-based GIMMS product (Pinzon & Tucker, 2014). More recently, MODIS has been used to develop the Enhanced Vegetation Index (Huete et al., 2002), which is increasingly used and has the advantage of being correlated with LAI but without saturation at high LAI values that hampers legacy products.

Vegetation functioning in terms of photosynthesis (and its relation to transpiration via stomatal conductance) can also be estimated from Solar-Induced Fluorescence, and interest has increased recently in the use of remote sensing derived estimates. For example, there have been global retrievals based on the Japanese Greenhouse gases Observing SATellite (Frankenberg et al., 2011) that have shown great promise in constraining estimates of the terrestrial carbon cycle, and applications to crop monitoring based on Global Ozone Monitoring Experiment-2 sensor (Guan et al., 2016). These early retrievals will be built upon with the recent launch of the NASA Orbiting Carbon Observatory-2 spectrometer and the upcoming Sentinel-5 Precursor mission that hosts the TROPOspheric Monitoring Instrument. These two sensors improve upon the resolution of Greenhouse gases Observing SATellite to 3 and 8 km, respectively, making retrievals relevant to decision-making. The upcoming (2022) ESA FLuorescence EXplorer is the first dedicated Solar-Induced Fluorescence mission.

The Sentinel-2 mission provides unprecedented information from which vegetation variables can be derived. The 13 spectral bands from visible and NIR to SWIR at a range of resolutions from 10 to 60 m are suitable for monitoring vegetation health. Sentinel-2 is providing data on several vegetation indices such as LAI, leaf chlorophyll content and leaf water content, and importantly, it is the first sensor to include bands in the *red edge*, which are suitable for estimating canopy chlorophyll and nitrogen content (Clevers & Gitelson, 2013). Again, NASA's proposed HyspIRI sensor is well suited to vegetation retrievals (section 4).

The recently launched Global Ecosystem Dynamics Instrument on the ISS will be the first high-resolution laser ranging sensor. The 2-year mission is focused on measuring forest canopy height, canopy vertical structure, and surface elevation, with research applications on the carbon balance and forest structure, but with potential also for observing water body levels and glaciers.

3.8. Current Use of RS for Decision-Making in the LAC Region

Remote sensing information is progressively finding its way into the decision-making context of countries in the region, although mostly focused on the use of precipitation and vegetation indices. Two types of usages can be identified. Single source remote sensing products are widely used for monitoring specific aspects of the water cycle on a regular basis. In this case, precipitation products are often used to complement the existing gauge measurement networks. A second type of use of remote sensing products for decision-making is integrated in modeling frameworks. In addition to the Latin American and Caribbean Flood and Drought Monitor (LACFDM) already mentioned, national efforts have been developed to generate locally relevant products for decision-making. We provide some examples of these two types of efforts.

3.8.1. Monitoring Precipitation

In the case of Peru, a merging procedure has been developed to combine the observed rain gauge network with the CHIRPS data set, providing a monthly rainfall product termed PISCO (Lavado et al., 2016), and which is designated as the official rainfall estimate for the country. A relevant data product for decision-making is the Standardized Precipitation Index, which has been defined by the World Meteorological Organization as an essential parameter for drought monitoring (World Meteorological Organization and Global Water Partnership, 2016). As a sufficiently long observation period of 30 years is required to determine the index, the observed rain gauge network is often insufficient for this purpose. For the same reason, only a limited number of RS products can be used for this purpose. Taking advantage of the high-resolution (0.05°) PISCO merged data set, Peru generates the Standardized Precipitation Index for drought monitoring which is made available through the National Drought Observatory (SENAMHI, 2018a). For flood risk management, the GPM-IMERG data set is currently used by SENAMHI to identify potential imminent flood hazards.

A similar effort was developed in Chile, using the PERSIANN rainfall product. Using the extensive database of more than 700 historical rain gauge stations (Figure 2a), a two-step procedure has been developed to calibrate PERSIANN in real time using a bias correction (Yang et al., 2016), in combination with a merging approach (Yang et al., 2017). This significantly improved the quality of the remote sensing product, and it has been therefore made available within the National Agroclimatic Observatory (Chile National Agroclimatic Observatory, 2018) for rainfall monitoring.

3.8.2. Integrated Crop, Drought, and Flood Monitoring

Vegetation indices are also actively used in a decision-making framework. Uruguay has developed the Instituto Nacional de Investigacion Agropecuaria (2018) monitoring system to identify the drought hazards in its agricultural sector, which uses the NDVI anomalies as one of its main indicators. A similar system has been implemented in Brazil, called AGRITIEMPO (2018), which uses a combination of station data and TRMM and MODIS remote sensing data. Mexico has implemented the national drought management plan PRONACOSE (Korenfeld-Federman et al., 2014), which includes the establishment of a national drought monitor. This has been built around the CHIRPS and NDVI data sets, providing continuous updates of drought conditions in the country. Mexico has adopted the Leaky Bucket model (Fan & van den Dool, 2004) from CPC/NOAA to provide soil moisture estimates for the national drought monitor. Several countries are experimenting with the integration of RS data to support early warning of water related hazards. An example is the daily monitoring and early warning of the main rivers of Peru, which uses the high-resolution PERSIANN precipitation data set (0.04°) to drive a hydrological model to evaluate potential flood hazards in the coming hours (SENAMHI, 2018b). The Food and Agriculture Organization has developed the Agricultural Stress Index System (Food and Agriculture Organization, 2018), which uses NDVI to calculate crop-specific drought stress during the growing season, including some forecast capabilities. National spin-offs of the global system are currently being set up, with case studies implemented in Nicaragua, Bolivia, Chile, and Peru during 2016 and 2017, in collaboration with their ministries of agriculture.

4. Future Planned and Proposed Missions

There is a wealth of planned and proposed missions that seek to continue our current capabilities, and several that have the promise for transforming the way we monitor the Earth's surface, with implications for improved water management, including drought and flood monitoring, in terms of accuracy, resolution, and repeat times. The impetus for new missions and opportunities is shaped by scientific community consensus such as the second U.S. National Decadal Survey (National Research Council, 2007) and latest National Decadal Surveys (National Academies of Sciences, Engineering, and Medicine, 2018), which prioritize research areas, observations, and potential missions to make those observations, including high-priority observations of relevance to WRM. Of relevance to WRM, designated program elements include for precipitation, changes in water storage on land, changes in glaciers and terrestrial vegetation, and recommendations for missions focused on land cover change and snow. Overcoming the main limitations of optical systems for day-night and all-weather retrievals, and low repeat intervals, and the spatial resolution limitations of microwave sensors, points at the use of combined systems and constellations of satellites. Here we provide a review of recently launched, upcoming and proposed operational and Earth Observation missions, including technical specifications of the retrieved products and planned dates.

4.1. Next Generation Geostationary Satellites

The GOES-R Series is the next generation of geostationary weather satellites for the United States, although it covers the Western Hemisphere and so is of relevance to LAC. The GOES-R series is a four-satellite program (GOES-R/S/T/U) operated by NASA/NOAA that will extend the availability of the operational GOES satellite system through 2036. The main instrument of relevance on the GOES-R satellites is the Advanced Baseline Imager, which has 16 spectral bands (compared to 5 on GOES): two visible channels, four near-infrared channels, and 10 infrared channels, and will have four times higher spatial resolution from 0.5 to 2 km depending on the band, with repeat time of 5–15 and 5 min over the CONUS. A retrieval mode will focus on two small regions with a 60-s repeat for storm activity that will be relevant to flooding.

Other next generation geostationary satellites that cover other continents, include the Meteosat Third Generation, which covers Europe and Africa, to be launched in 2019 and will be the first of the next generation up until 2038. Fengyun-4 is a series of satellites first launched in 2016 operated by the China Meteorological Agency covering eastern Asia and Australasia. Himawari Third Generation is operated by the Japanese Meteorological Agency to cover operational weather monitoring for the Asia-Pacific region.

4.2. The JPSS

JPSS is an upcoming polar-orbiting operational environmental satellite system jointly run by NOAA and NASA. Satellites will provide global coverage twice per day, and includes a range of sensors including the Visible Infrared Imaging Radiometer Suite (VIIRS). The VIIRS multispectral instrument was first launched in 2011 aboard the NASA/NOAA Suomi National Polar-orbiting Partnership satellite with the intention of bridging between MODIS and the operational Joint Polar Satellite System (JPSS). VIIRS will be one of the instruments on the JPSS. Its large swath width (3,060 km) provides near-global coverage in 1 day. The sensor measures in 22 bands in the VIR spectra. With a spatial resolution between 375 and 750 m depending on the band wavelength. VIIRS builds on AVHRR and MODIS to provide daily time series of multispectral data with applications in energy and water balance, vegetation dynamics, land cover land use change, and the cryosphere. Of relevance here are retrievals of LST and ET, and vegetation parameters such as fPAR, leaf water content, and LAI, and snow cover products. For example, a global 400-m VIIRS-based ET product is under development based on Hain et al. (2017), beginning with regional data sets for the Middle East/North Africa, United States, and Brazil.

4.3. Hyperspectral Missions

Several hyperspectral imaging missions are planned or have been proposed, which can help improve retrievals of snow and vegetation properties, and deliver new water quality and soil property products, through continuous spectral sampling of the VNIR and SWIR regions. NASA's proposed HyspIRI has an imaging spectrometer measuring from the VSWIR range in 10-nm contiguous bands and a multispectral imager measuring from 3 to 12 μm in the TIR range at 60-m resolution at nadir and revisit of 19 and 5 days, respectively. This has a number of applications, including for snow retrievals, vegetation monitoring, and ET (Lee et al., 2015). Other missions include the Italian Space Agencies PRISMA demonstrator mission (Stefano et al., 2013), which uniquely combines a hyperspectral imager (~250 bands, 400–2,500 nm, 30-m spatial resolution), and a panchromatic imager (5-m spatial resolution), that together can further enable retrievals relevant to water quality of inland waters. The German Space Agency EnMAP mission (Guanter et al., 2015) is a hyperspectral imager in the spectral range of 420–2,450 nm, with bands of 10- to 40-nm width, at 30-m spatial resolution, with a revisit time of at least 4 days, with potential research applications in crop and forest monitoring, inland and coastal waterways, and soil science, among others.

4.4. Groundwater From GRACE-II and NISAR

The GRACE Follow-On (GRACE FO) mission launched in May 2018 and will provide continuation of the GRACE record, eventually bridging to the next generation GRACE-II mission. GRACE FO is technologically similar to GRACE, using accurate measurements of the intersatellite range between two coplanar, low-altitude polar orbiting twin satellites using a K/Ka-Band microwave tracking system, and the continuation of radio occultation measurements. GRACE-II is expected to launch in 2020 and proposes a technology upgrade from the microwave interferometer to a laser (that will be tested on GRACE FO) to provide much higher spatial resolution (~10,000 km^2 compared to 500,000 km^2 for GRACE and GRACE FO) and accuracy than the microwave instrument. The pair of satellites will be flown at a lower altitude with a drag free system. This will enable perhaps an order of magnitude improvement in spatial resolution, making GRACE II directly applicable to a wider range of water resource characterization and management activities globally.

The further use of SAR sensors for estimating groundwater through the minute variations in surface topography will continue with planned missions such as the joint U.S.-Indian NASA-ISRO Synthetic Aperture Radar (NISAR) polar-orbiting mission, due to launch in 2021. This will carry a L-band SAR and S-band SAR and provide meter-scale retrievals of land surface height that can indicate groundwater storage changes.

4.5. SWOT

The upcoming SWOT mission that is set to launch in 2021 will address many of the issues associated with the along-track retrievals of current altimeters by providing images of surface height using a Ka-band radar interferometer, for a 120-km swath for river reaches and water bodies that are 100 m or wider (Biancamaria et al., 2015; Pavelsky et al., 2014). As well as surface water heights, it will also provide measurements of water level slopes and inundated areas, at a repeat interval of about 21 days, which will provide about two measurements for each point within that period. The biggest challenge for SWOT is the derivation of channel depths and discharge, and several methods have been tested based on various approaches from simple methods based on Manning's equation that would use river width and slope from SWOT, to more complex methods based on approximations of the 1-D Saint Venant equations that use SWOT observations of water surface elevation, width and slope to derive depth and discharge (Durand et al., 2016). All these methods rely on in situ data to estimate depth and flow velocities limiting their universal application, particularly in ungauged regions. Model assimilation approaches will undoubtedly be necessary because of the low temporal repeat of the retrievals and the need for continuous measurements of discharge (e.g., Munier et al., 2015). Much work has been done in this area for current sensors with improvements in model predictions compared to in situ gauges in a variety of settings (e.g., Paiva et al., 2013). NASA's upcoming IceSAT-2 mission will complement SWOT; although it is focused on measuring ice sheets it will provide information for water body elevation.

4.6. Water Cycle Observation Missions

China has targeted the Water Cycle Observation Missions for a launch in 2020 (Dong et al., 2016). The system will measure a range of relevant variables including soil moisture, SWE, freeze-thaw, and precipitation, using simultaneous measurements from active and passive microwave sensors for a range of frequencies. These are the IMI fully polarized interferometric radiometer that will provide soil moisture (as well as ocean salinity); the dual-frequency polarized scatterometer for retrievals of SWE and freeze/thaw; and 3 polarimetric microwave imager at 6.8–89 GHz that will resolve temperature, rainfall and water vapor. This approach is likely essential to help address the problems of leveraging from nonwater cycle focused missions with suboptimal frequencies, lack of supporting data, and independent retrievals for different variables.

4.7. BIOMASS

BIOMASS (ESA, 2012b) is an ESA planned satellite focused on quantifying forest biomass and height globally (tropical, temperate, and boreal), including disturbance and forest flooding, with a launch date for 2020, and expected mission of 5 years. It will carry a P-band SAR, with a resolution of 50–60 m, although limited to global coverage every 25 days. It also has applications to land and glacier topography. This will be first global P-band mission.

5. Challenges, Opportunities, and Outlook

The wealth of information available from past and current satellite missions has enabled the routine evaluation and monitoring of hydrological variables that are being used for or have the potential for management of water resources and the impacts of hydrological hazards. These do come with challenges that are intense topics of current research to understand how to improve retrievals and translate to applications. The gamut of newly launched and upcoming missions, from agencies, commercial enterprises, and the private sector, has the potential to transform this capability to address many of these challenges. At the same time, new challenges are emerging, particularly in how we handle the tremendous streams of data and interpret them for water resources applications. Key challenges of relevance to WRM are discussed next, followed by ongoing research and emerging opportunities to address these challenges:

5.1. Challenges

5.1.1. Validation and Hydrological Consistency

Remote sensing retrievals are most often developed using a retrieval model that brings with it errors due to uncertainties in how to represent the known physical processes and parameterize these, and due to unknown processes and feedbacks. Validation of retrievals, and potentially calibration of the models, is therefore vital. Unfortunately, this is not done as comprehensively as one would like due to the lack of in situ data that the remote sensing retrieval attempts to supplement. Individual retrievals are generally validated against in situ data that have a limited footprint or are region specific, and in isolation from other variables of the water balance (Zhang, Zhang, et al., 2017). However, this often represents a disjoint picture from the application context, which may require data over large river basins, for multiple variables, in real time, and so on. This is further complicated by the fact that remotely sensed variables have unique spatial and temporal characteristics that make it difficult to use multiple variables in concert without some kind of downscaling or integration. For example, estimating the water budget across a river basin from remote sensing could require integrating coarse scale estimates of total water storage from GRACE (~500 km, 30 day), precipitation from TMPA (25 km, 3-hourly), ET from MODIS (1 km, once daily) and streamflow (single river reach, 15 day). However, the limited assessment to date of the consistency among remotely sensed variables at scales relevant to WRM shows a range of errors across variables and nonclosure of the water budget when combined (e.g., Armanios & Fisher, 2014; Azarderakhsh et al., 2011; Gao et al., 2010; Sahoo et al., 2011; Sheffield et al., 2009). As an example, Figure 9 shows the representation of the 2005 drought in the Amazon basin for all components of the water budget and vegetation, based on a suite of satellite products and also compared to outputs from a land surface model. There are obvious resolution differences between, for example, the TMPA (0.25°) and the GPCP (1.0°) precipitation products, and between the GRACE retrieval of total water storage (~500 km) and the AMSR-E-based surface soil moisture (40 km; as well as differences in the physical variable being represented), which ensure that direct comparisons are difficult. However, the qualitative consistency among related products in representing drought conditions (e.g., less precipitation is consistent with less surface soil moisture and total water storage) is encouraging and physically reasonable (e.g., higher Rnet in drought periods because of less precipitation and clouds, leads to positive ET anomalies). A range of opportunities exist to overcome the limitations, as discussed below, including integrating retrievals with in situ observations and observation-based analyses, or with modeling via assimilation.

5.1.2. Resolution, Continuity, and Latency

WRM applications generally require information at the catchment scale, which can vary from a few square kilometers to several hundred thousand. At the same time, information may be needed for subcatchments or gridded to be consistent with models and other data sets. For remote sensing retrievals based on TIR sensors, this is not generally a problem, but for microwave based retrievals, such as for soil moisture, the resolution is too coarse (10s km) for most applications. Downscaling of soil moisture data via merging with higher-resolution active microwave radar and TIR imagery, via statistical models or via assimilation into physical models is therefore necessary (Peng et al., 2017).

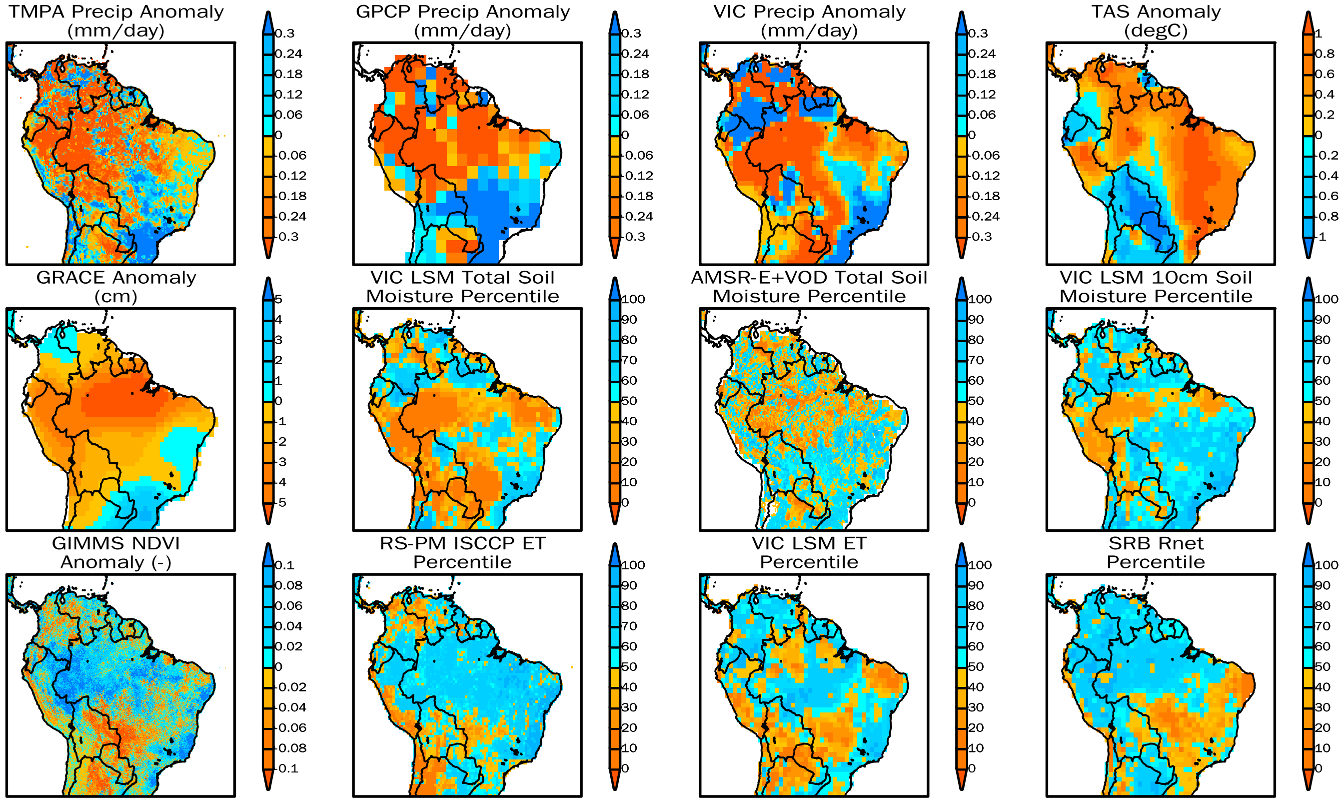

Figure 9. Multisensor view of the August–September 2005 Amazon basin drought. (top row) Anomalies or percentiles of precipitation from TMPA, GPCP, PGF (Princeton Global Forcings, Sheffield et al., 2006; http://hydrology.princeton.edu/data.php, which is a blend of reanalysis and CRU monthly data) and air temperature from PGF. (middle row) Anomalies or percentiles of GRACE total water storage, modeled 2-m soil moisture from the VIC land surface model (forced by the PGF; http://hydrology.princeton.edu/data.php), AMSR-E soil moisture (with account for vegetation optical depth), and VIC top 10-cm soil moisture. (bottom row) Anomalies or percentiles of AVHRR NDVI, ISCCP-based ET, VIC ET, and SRB net radiation. Anomalies for August–September 2005 are calculated based on the monthly anomalies calculated for the time period of each data set. Percentiles are also based on monthly values estimated from the empirical cumulative density function over the same time period for each data set.

Conversely, the temporal repeat (and cloud interference) of TIR retrievals hampers their use for daily scale decision-making or quantifying rapid changes, but these can be complemented by higher temporal repeat retrievals based on sensors on polar-orbiting satellites. This has been successfully used for precipitation retrievals, which leverage the accuracy of microwave retrievals and the higher resolution of TIR retrievals. Merging of soil moisture data is less well developed for applications, but progress has been in understanding the potential (Peng & Loew, 2017).

Data record length and temporal consistency are also a challenge for WRM, which rely on long-term and homogeneous time series to identify extreme events and calculate risk, especially for planning and engineering design. The use of remote sensing based data is therefore generally hampered by short mission lengths, and continuity issues for ongoing programs, for example, for Landsat and for operational weather monitoring. Similar constraints do also apply to in situ data, for which even several decades of data may not encompass the likely range of extremes that are possible (Klein Tank et al., 2009). In addition to ongoing programs, efforts are under way to stitch together data from multiple sensors (e.g., the ECV soil moisture record, Dorigo et al., 2017; the HIRS-based LST record, Siemann et al., 2016), but careful intersatellite calibration is necessary, which is not a trivial task.

Latency refers to how near to real-time data are available. This is vital for some WRM applications, in particular for drought and flood warning, and irrigation forecasting. For example, GPM IMERG products are provided at latencies of a few hours, with potential to access some subproducts within 30 min, which is approaching real-time monitoring. The latency of other products can be longer, due to temporal repeat and cloud cover, or by design. Providing data in near real time is also a challenge to the supporting computational and network infrastructure (section 5.2.4).

5.1.3. Adaptation to Applications

Key to the uptake of RS to support WRM is the adaptation of remote sensing products to planning, design, and operational activities. There are many technical and human barriers to translating research products into retrospective products that can be used for design and planning, or operational products that can be used for day-to-day management and early warning, as discussed above. This depends greatly on user needs in terms of the spatial and temporal consistency, accuracy, latency, and so on, as well as the technical capacity of the user. For example, informal surveys by the authors with agency staff from several LAC and African countries carried out during training workshops on the use of RS and models for drought monitoring, indicate that accuracy, timeliness, and spatial representativeness of information are key requirements to help improve WRM in their region. This is echoed by others (e.g., Schaeffer et al., 2013) that indicate that cost, accuracy, continuity, and agency approval for using RS were the key concerns for water managers when using RS-based water information. Cost issues may be related to previous experience with RS imagery; for example, Landsat data were previously charged for by the U.S. Geological Survey. In terms of accuracy, quantitative error estimates are required for uptake, and users are most interested in site-specific evaluations that are not always available. Evaluations need to take into account in situ measurement errors and scale mismatches between in situ and RS data. At the same time, users also need to identify their accuracy requirements to RS providers. Concerns about continuity are often cited because of worries that products will not be available in the future, and therefore efforts are needed by RS agencies to ensure that continuity is provided including standardizing retrieval methods, data formats and access, and providing intersatellite calibration. Continuity also relates to challenges in transitioning to using different data sources that may conflict with existing WRM methods and practices that are based on traditional, in situ measurements.

Successful implementation of locally tailored applications often suffers from several bottlenecks in local end-user agencies: lack of sufficient human and technical capacity, lack of a stable environment to ensure continuity, maintenance and updating, lack of funding, poor internet connection, and others. Lack of capacity and human resources is identified as a key constraint to the uptake of RS information (World Bank Group, 2018). There is a need for training in methodologies, software, and databases, and backing from agency management is vital to provide the education, training and support. As RS information becomes more complex, especially for the uptake of more recent research products that do not have a long legacy of provision to a wide variety of users, training in specific software and methodologies is required, and this should be focused on WRM applications rather than generic RS techniques. On the other hand, RS agencies should provide products that are ready for analysis, in standardized formats. The use of user friendly platforms such as the LACFDM and the use of cloud computing services can remove much of this overhead (see later). However, this raises questions about the sustainability of products and data platforms, in particular who should fund them, who decides what is done, and for whom?

Overall, effective dialog is needed between scientists who produce, evaluate, and apply RS information, and managers and stakeholders who use this information to make decisions. Often there is a disconnect between research carried out in academic institutions and management agencies, even within the same country. This is because water management is site specific and is mediated by the behavior or local actors and institutions, and many applications will need to be locally customized (adapted, calibrated, validated with ground data, etc.) to address the local needs of management. Stronger partnerships between agencies and identified academic institutions are needed. Application scientists should continue to understand user needs; stakeholder involvement and codevelopment of products is not always feasible but should be done where possible. Transparency in RS methodologies, and even transition to standardized approaches so that users can readily understand how products are developed is also required.

5.2. Opportunities

5.2.1. Integration With In Situ Data and Modeling

Integration with in situ data and hydrological models is perhaps the most promising way to leverage remote sensing data for WRM. For example, assimilation of soil moisture data into hydrological models can improve predictions of soil-column water, ET, and streamflow (Brocca et al., 2012; Chen et al., 2011; Ridler et al., 2014). The use of remote sensing-based actual ET estimations to constrain hydrological models can also significantly improve simulations (Roy et al., 2017). Assimilation of snow covered area and SWE into models has a long legacy and is being used to forecast seasonal water availability for systems that rely on seasonal snowpack for water supply (e.g., western United States). Integration of in situ data from meteorological networks can be used to improve satellite based gridded products (Chaney et al., 2014). Bias correction of satellite-based precipitation with just a handful of gauges can significantly improve hydrological predictions (Serrat-Capdevilla et al., 2014). Where national networks are less prevalent, low-cost sensors (e.g., Buytaert et al., 2014) and even nontraditional data networks (e.g., Eilander et al., 2016) can also provide data for correcting and updating retrievals.

One promising approach is to use the water budget to enforce closure by distributing errors across individual water budget components based on their errors (e.g., Pan et al., 2012; Zhang, Pan, et al., 2017). These approaches do require an estimate of errors of individual products, but comparison with competing and alternative products (e.g., from remote sensing, modeling and gridded observational analyses) through methods such as triple colocation (e.g., Anderson, Zaitchik, et al., 2012) can provide a first-order approximation.

5.2.2. Forecasting and Early Warning

Hydrological forecasts can play an important role in early warning of hazards, complementing hydrological monitoring based on remote sensing, and in turn being initialized by land surface states based on remote sensing. Climate forecasts have advanced in terms of skill and resolution over past decades such that they can provide some predictability in regions that have strong teleconnections with ocean temperatures, and at spatial resolutions (order of 1–10 km) required for decision-making. For example, forecasts of El Niño–Southern Oscillation from dynamical climate models are now outperforming statistical forecasts (Barnston et al., 2012), and with potential for skillful forecasts of regional climate in the tropics and subtropics (e.g., Kumar et al., 2013). In midlatitudes, skillful forecasts are more elusive because of the high variability of weather systems, but longer-lead forecasts for temperature at least are emerging (e.g., McKinnon et al., 2016; Scaife et al., 2014). Remote sensing can play a direct role in enhancing hydrological predictions via updating of initial conditions. Data needed to initialize forecast models (e.g., soil moisture, snow, and river levels/discharge) can be derived from remote sensing and many studies have shown the benefits of updating hydrological forecasts (Hirpa et al., 2013; Lü et al., 2016) particularly increasing predictability in snow-dominated and dry regions of the world (Shukla et al., 2013). Several experimental, operational systems that provide satellite-based monitoring and initialization of hydrological forecasts include the LACFDM (2017), African Flood and Drought Monitor (Sheffield et al., 2014), and the European Flood Alert System (Thielen et al., 2009).

5.2.3. Commercial Satellites

An increasingly important source of remote sensing information is from the commercial sector, in particular constellations that can overcome the trade-offs between resolution and repeat interval (McCabe et al., 2017). Notable recent and upcoming missions include the following:

1. *Planet Labs* launched demonstration CubeSats (miniaturized satellites) called Doves in 2013 and subsequently launched several *Flocks* of Dove that provides global optical imagery coverage at 5-m resolution, including 88 Doves in one launch in 2017.
2. *The UrtheDaily Constellation* is a constellation of eight satellites providing global coverage that provides multispectral imagery at 5-m resolution, daily (10:30 a.m.). The expected launch is 2018.
3. *OptiSAR* is a proposed constellation of eight pairs of satellites, one carrying an optical imager and video (50-cm resolution) and the other a SAR providing 1-m X-band and 5-m L-band images. This combination will have global at least once daily coverage, with day/night retrievals in the presence of clouds. The combination of optical and SAR allows for the calibration of the SAR based on the optical images. The constellation is proposed for operations as early as 2020.
4. *Pangeo Alliance*. Of interest is the provision of combined access to various sensors via the Pangeo Alliance that currently brings together eight Earth Observation operators to provide multispectral imagery and high-resolution video, globally and daily. Table 4 lists the sensors in the alliance and their characteristics.

5.2.4. Analytical Platforms and Data Services

One of the biggest challenges is the provision of services to access and utilize the voluminous amounts and rapid flow of information being generated by current and planned missions. For example, the Sentinel-1 satellite delivers approximately 1 TB of raw data each day, which translates into 10 PB (1016 bytes) over the expected lifetime of the mission (Wagner et al., 2009). When the derived data sets for various

Table 4
Characteristics of Current and Planned Sensors Within the Pangeo Alliance (http://www.pangeo-alliance.com/)

Sensor	Country	Sensor type	Spatial resolution	Spectral bands	Swath width	Launch date
Deimos 1	Spain	Optical MR	20 m	3	650 km	2009
Landmapper BC	United States	Optical MR	20 m	3	220 km	2016
KazSTSAT	Kazhakstan	Optical MR	18 m	6	300 km	2017
Theia	Canada	Optical MR	5 m	4	50 km	2013
KazEOSat 2	Kazhakstan	Optical MR	5 m	5	77 km	2014
Landmapper HD	United States	Optical HR	2.5 m	5	25 km	2017
DubaitSat 1	UAE	Optical HR	2.5 m	Pan +4	20 km	2009
TH-1	China	Optical HR	2 m	Pan +4	60 km	2010, 2012, 2015
Deimos 2	Spain	Optical VHR	75 cm	Pan +4	12 km	2014
DubaitSat 2	UAE	Optical VHR	1.0 m	Pan +4	12 km	2013
KhalifaSat	UAE	Optical VHR	70 cm	Pan +4	16 km	2018
KazEOSat 1	Kazhakstan	Optical VHR	1.0 m	Pan +4	20 km	2014
TeLEOS 1	Singapore	Optical VHR	1.0 m	Pan	12 km	2015
Iris	Canada	Video 4 K	1.0 m	3 (RGB)	6 × 4km	2013

applications (hydrological, water resources, agriculture, health, etc.) are added, this number will increase further, which becomes a logistical and computational challenge likely beyond any single data facility. Another example is the Landsat program, which now represents an almost 40-year record and over a PB of data. NASA facilities process over 5 TB of data per day and the NASA Earth Observing System Data and Information System holds over 7.5 PB (as of 2015) of satellite data across connected data centers (Sugumaran et al., 2015). This flood of *big data* poses many challenges in how we collect, manage, store, archive, analyze, visualize, and distribute it (Sugumaran et al., 2015).

High-performance computing that encompasses the concepts of supercomputing, cluster computing, and distributed/grid computing, is required to meet these challenges, yet traditional facilities at research institutions and government agencies are out of the reach of the majority of users, despite large strides in the provision of data management and visualization tools by large data centers. New approaches are therefore needed that draw from the power of parallel computing but that are affordable and accessible. The solution is likely to be cloud computing services that provide "ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources" (Horak et al., 2008; Mell & Grance, 2011). Cloud computing also encompasses the concepts of distributed and grid computing but refers more generally to resources that are scalable and available on demand. Cloud computing also allows sharing of data and code that has important implications for knowledge transfer and capacity building.

Some examples of commercial pay-as-you-go cloud computing services are Amazon's Elastic Compute Cloud (EC2) that is accessible via Amazon Web Services, Google's Cloud Platform, and Microsoft's Azure, which variously provide access to the computing infrastructure (e.g., virtual machines such as Google's Compute Engine) that requires the user to install, configure, and run their own processing software, or computing platforms that abstract the software and file system from the operating system (e.g., Apache's Hadoop), or software platforms that abstract into a single software application (e.g., Google Earth Engine). The scalability and on-demand nature of these resources, coupled with relatively low cost, are key benefits. In particular, the abstraction of the hardware and operating/file system is key to enabling users to access the vast quantities of remote sensing information. These platforms are increasingly being leveraged for analyzing satellite imagery and more recently for WRM applications, such as the Climate Engine that uses Google Earth Engine for drought monitoring and other natural resources management applications (Huntington et al., 2017). Despite the provision of reliable, and scalable access to distributed computer power, the overhead of training users should not be underestimated, especially for applications that are not straightforward parallel processing of subsets of satellite imagery.

5.3. Outlook

Satellite remote sensing is now able to provide near-real-time retrievals of nearly all components of the terrestrial water cycle, albeit with many challenges including those related to accuracy, consistency, continuity, and utility. Although much work is needed to enable and improve approaches for retrieving groundwater, water quality, surface water levels, and river flows, most of these retrievals are also global in coverage, and at the spatial, temporal, and spectral resolutions to resolve hydrological processes and their interaction with human activities. They are therefore well poised to provide information for WRM for operational and tactical decision-making. In particular, satellites can provide information in regions where in situ data are scarce, unreliable, or unavailable as a real-time information source. These opportunities should be leveraged to also support disaster risk management and reduction. Remote sensing products are progressively being integrated in national monitoring and early warning systems at the national and regional level, as the examples show in section 3 for the LAC region.

To fully realize the potential, however, requires an understanding of the multiple, independent, complementary, and competing data products, and their utility for a range of diverse management applications, including flood/drought risk assessment and the monitoring of water availability. Specifically, capacity needs to be built to work with satellite data and translate it into information that can inform the decision-making process. This, in turn, requires continuing and building on existing training programs and initiatives (e.g., UNESCO International Hydrology Programme capacity development initiatives; NASA SERVIR, ARSET, and DEVELOP programs; ESA Tiger Initiative) to translate the often complex satellite data into formats and data delivery platforms that are easy to use for a range of users. Furthermore, a large gap remains between the availability of these products, and their uptake for decision-making. Therefore, an opportunity remains to engage more actively with the national stakeholders to strengthen capacities to use these remote sensing products, especially in data scarce regions, in order to build solutions and capabilities for monitoring and early warning applications of natural hazards in support of effective disaster risk reduction policies at the national level. To this effect, and to keep up with this fast-evolving field, the role of knowledge networks linking government agencies, universities and research centers, and international development organizations is essential.

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