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Amazon Hydrology From Space: Scientific Advances and Future Challenges

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Key Points:

- Integrated view of scientific advances in Amazon hydrology with remote sensing
- Expected progress to understand the water cycle, aquatic ecosystems, and environmental changes with upcoming hydrology-oriented missions
- Need to translate advanced knowledge from remote sensing to support water management and environmental governance

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Abstract As the largest river basin on Earth, the Amazon is of major importance to the world's climate and water resources. Over the past decades, advances in satellite-based remote sensing (RS) have brought our understanding of its terrestrial water cycle and the associated hydrological processes to a new era. Here, we review major studies and the various techniques using satellite RS in the Amazon. We show how RS played a major role in supporting new research and key findings regarding the Amazon water cycle, and how the region became a laboratory for groundbreaking investigations of new satellite retrievals and analyses. At the basin-scale, the understanding of several hydrological processes was only possible with the advent of RS observations, such as the characterization of "rainfall hotspots" in the Andes-Amazon transition, evapotranspiration rates, and variations of surface waters and groundwater storage. These results strongly contribute to the recent advances of hydrological models and to our new understanding of the Amazon water budget and aquatic environments. In the context of upcoming hydrology-oriented satellite missions, which will offer the opportunity for new synergies and new observations with finer space-time resolution, this review aims to guide future research agenda toward integrated monitoring and understanding of the Amazon water from space. Integrated multidisciplinary studies, fostered by international collaborations, set up future directions to tackle the great challenges the Amazon is currently facing, from climate change to increased anthropogenic pressure.

Plain Language Summary The Amazon basin is the largest river basin in the world, characterized by complex hydrological processes that connect high rates of precipitation, extensive floodplains, dense tropical forests, complex topography, and large variations in freshwater storage and discharge. It plays a key role in the water, energy, and carbon cycles and interacts with the global climate system. Earth observations have played a major role in supporting research in Amazon hydrology, and the characterization of several hydrological processes was only possible with the help of remote sensing data. The basin is now facing great risk under current climate change and increased anthropogenic pressure and the resulting environmental alterations require a better understanding of the overall basin's water cycle across scales. We review the strengths and limitations of observations from satellites in the context of the current and upcoming hydrology-oriented satellite missions, and we make recommendations for improving satellite observations of the Amazon basin water cycle, along with an interdisciplinary and stepwise approach to guide research for the next decades.

1. Introduction

The Amazon River basin is a major hydrological system (~6 million km^2) with diverse rivers, floodplains, and wetlands (Junk et al., 2011; Reis et al., 2019, Figure 1). It spans seven countries and hosts four of the 10 largest rivers in the world, namely the Solimões-Amazonas, Madeira, Negro, and Japurá rivers (Figure 2). It receives high annual rainfall (~2,200 mm year^{-1}, Builes-Jaramillo & Poveda, 2018; Espinoza et al., 2009) and around 30%–40% of the precipitation in the basin is recycled by local evapotranspiration (Eltahir & Bras, 1994; Salati et al., 1979; Satyamurty, da Costa, & Manzi, 2013) providing moisture to southern parts of South America. The Amazon River flows into the Atlantic Ocean with an average annual discharge of 206×10^3 m^{3}s^{-1} (Callède et al., 2010), amounting to almost 20% of the total global freshwater reaching the ocean annually and exports a large number of sediments to the ocean (1.1×10^9 tons per year; Armijos et al., 2020).

The high rates of precipitation, evapotranspiration and large variations in freshwater storage and river discharge make the Amazon basin a key player in the global climate system, with large contributions to the water, energy, and carbon cycles (Gash et al., 2013; Gatti et al., 2021; Nagy et al., 2016). Amazon surface waters, for instance, are a major source and sink of carbon dioxide (Abril et al., 2014; Amaral et al., 2020; Guilhen et al., 2020; Raymond et al., 2013; Richey et al., 2002) and the largest natural geographic source of methane in the tropics (Kirschke et al., 2013; Melack et al., 2004; Pangala et al., 2017; Pison et al., 2013). Seasonal variations in the water contribute to the formation of tropical forests (Leite et al., 2012), maintain high aquatic productivity (Melack & Forsberg, 2001) and biodiversity (Junk, 1997; Junk et al., 2010), and influence fish distributions and fisheries yield (Junk et al., 2010; Lobón-Cerviá et al., 2015; Figure 1). The Amazon hosts ~40% of the world's tropical forest and ~15% of global land biodiversity (Marengo et al., 2018). It is also the home of local people that rely on rivers as transportation corridors, and utilize these environments for their subsistence (Anderson et al., 1991; Campos-Silva et al., 2020; Endo et al., 2016). Amazon also serves the broader South American population in terms of energy, food, and other forest products.

The region is now facing risks under climate and anthropogenic changes, and changes in Amazon hydrology could have substantial impacts globally (Jimenez et al., 2019). In the past decades, the basin experienced several intense climatic events, such as extreme droughts and floods, with no equivalent in the last 100 years (Barichivich et al., 2018; Marengo & Espinoza, 2016). Severe droughts can lead to environmental disturbances, from increased fire occurrence (Zeng et al., 2008) to abrupt shifts in fish assemblages (Röpke et al., 2017). Moreover, the accumulated negative impacts of increased human interventions across the region, such as damming (Forsberg et al., 2017; Latrubesse et al., 2017), deforestation (Arias et al., 2020; Coe et al., 2009; Gutierrez-Cori et al., 2021; Leite-Filho et al., 2020; Leite et al., 2012), fires (Aragão et al., 2008; Libonati et al., 2021; Xu et al., 2020; Zeng et al., 2008), and mining (Abe et al., 2019; Lobo et al., 2015), will possibly trigger major modifications that could affect the Amazon water cycle.

Characterizing and understanding the dynamics of the Amazon water cycle is of primary importance for climate and ecology research and for the management of water resources. Consequently, there is a need for comprehensive monitoring of the spatial-temporal dynamics of the Amazon water cycle components and how they interact with climate variability and anthropogenic pressure. In large and remote tropical watersheds such as the Amazon, in situ observational networks are difficult to operate and maintain, and remote sensing observations have brought opportunities for monitoring the various components of the water cycle, although many technical challenges still need to be overcome.

While the Amazon basin was in the spotlight of international scientific discussion during the last decades, the understanding of Amazon hydrology coevolved with another groundbreaking field: the remote sensing (RS) of the terrestrial water cycle. In this context, the Amazon basin has been an ideal natural laboratory for the seminal development of RS techniques with the advent of Earth observations (EO) and these advances have fostered the scientific understanding of Amazon hydrology, ecosystems, and environmental changes. For example, the first applications of altimeter and gravimetric satellites to characterize, respectively, surface water elevation (Guzkowska et al., 1990) and total water storage variations (Tapley et al., 2004) were performed in the basin due to its wide river and large spatial and temporal changes of freshwater. Pioneering RS applications also include microwave, synthetic-aperture radar (SAR), and interferometric mapping of large-scale flood inundation and characterization of sediment dynamics (Alsdorf et al., 2000;

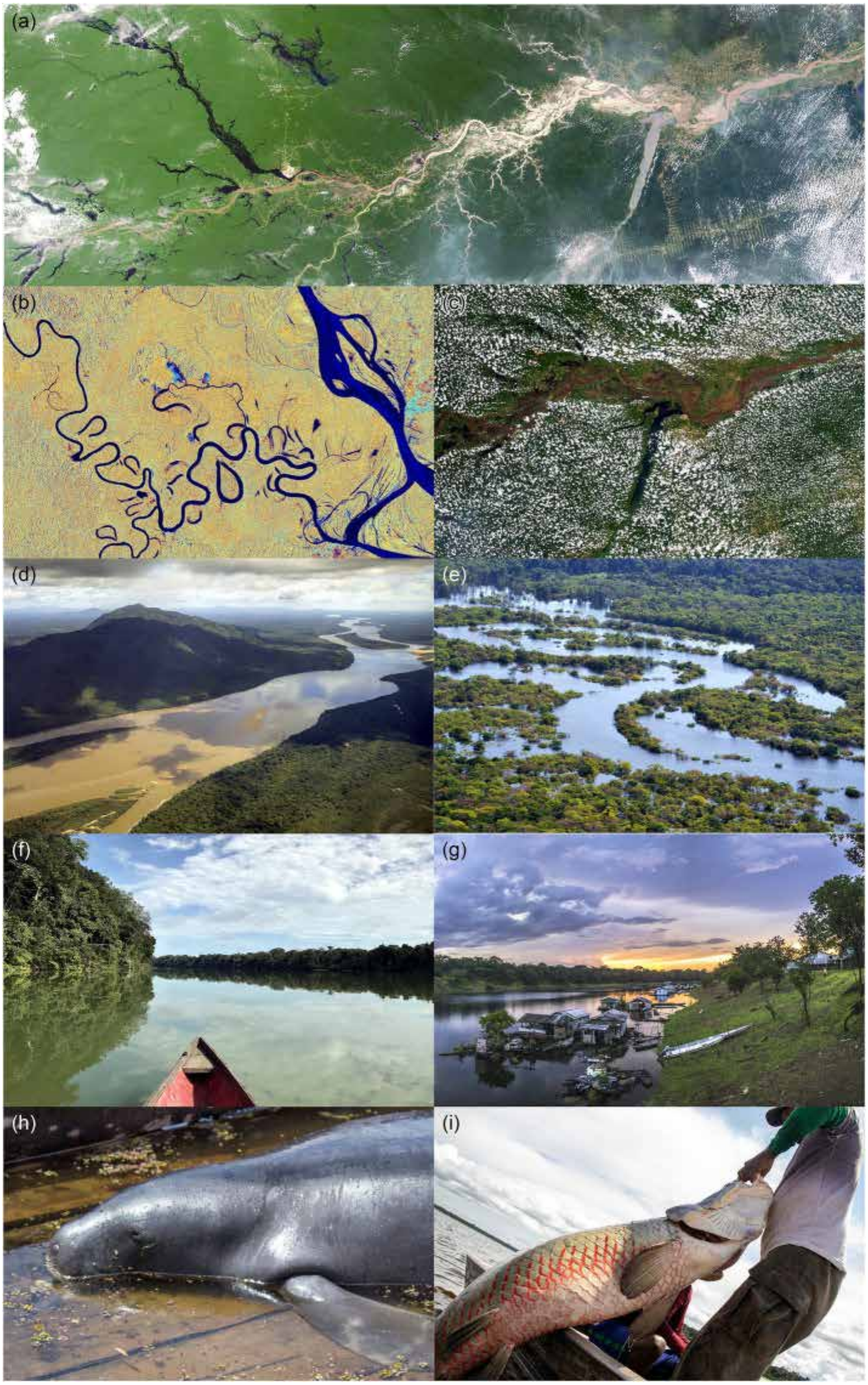

Figure 1. Amazon River basin diversity. (a) Moderate Resolution Imaging Spectroradiometer (MODIS) image of the central Amazon basin, characterized by large floodplains (Source: National Aeronautics and Space Administration [NASA] catalog; https://visibleearth.nasa.gov/images/62101/the-amazon-brazil/62104l); (b) Sentinel-1 image of rivers and lakes of the upper Solimões River (Source: ESA catalog; https://www.esa.int/ESA_Multimedia/Images/2020/09/Amazon_River); (c) MODIS image showing the reduced cloud cover over water bodies (Source: NASA catalog; https://earthobservatory.nasa.gov/images/145649/mapping-the-amazon); (d) Aerial view of Branco River (Photo by Thiago Laranjeira); (e) Floodplain during the high water (Photo by João Paulo Borges Pedro); (f) Channel (Photo by Jefferson Ferreira-Ferreira); (g) Community at the river bank (Photo by Thiago Laranjeira); (h) Manatee (Photo by Amanda Lelis); (i) Arapaima (Pirarucu) fish, the largest scaled freshwater fish in the world (Photo by Bernardo Oliveira).

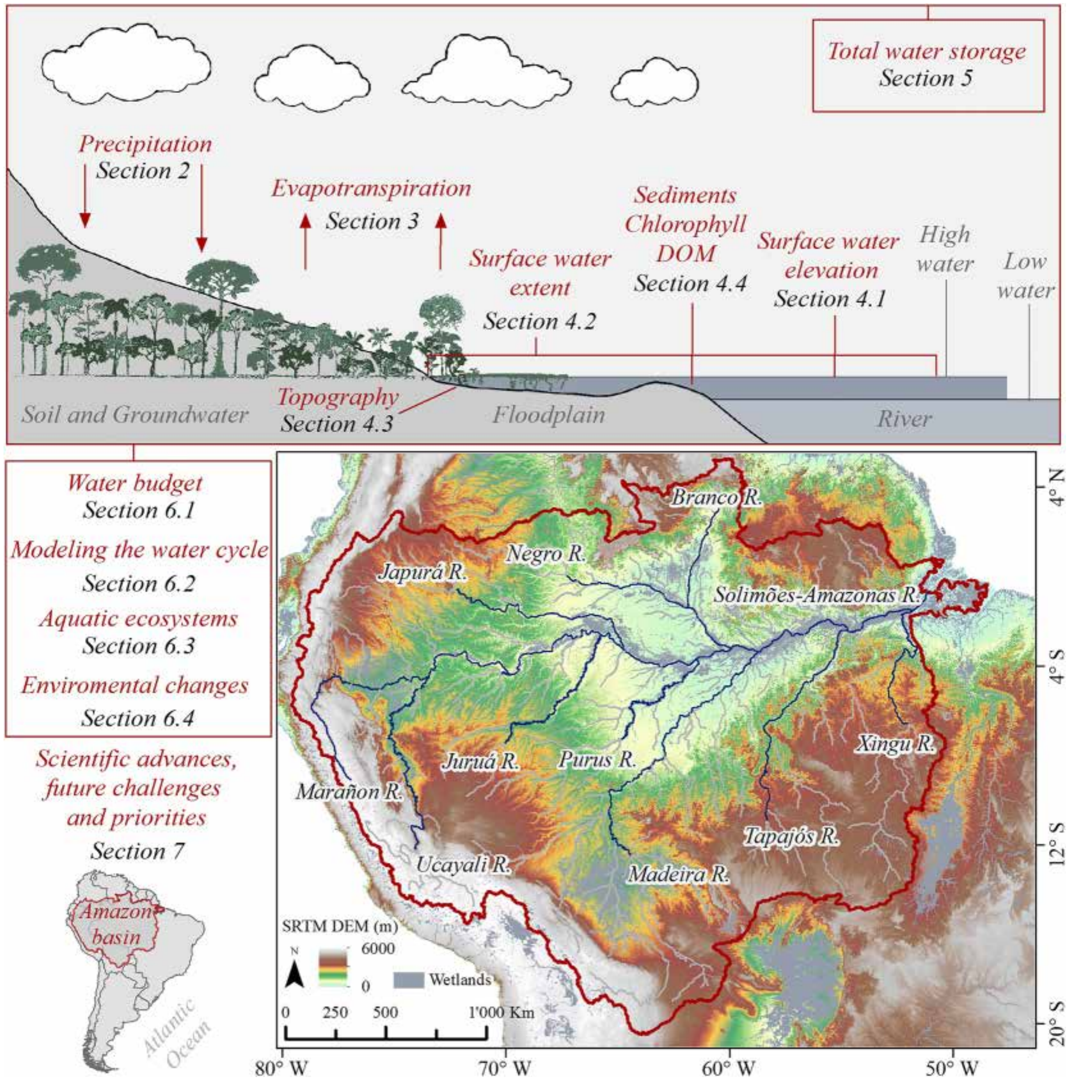

Figure 2. Location of the Amazon basin in South America, and representation of the hydrological variables observed by remote sensing techniques, with the respective section numbers as addressed in this review.

Hess et al., 2003; Mertes et al., 1993; Sippel et al., 1994). Since then, several applications using RS data have been carried out in other basins worldwide (e.g., Alsdorf et al., 2021). All these important developments have been done by a diverse community of scientists with different interests and views on the Amazon water cycle, and surprisingly, there is a lack of review analyzing the continuous growth of publications that make use of RS observations to study the hydrology of the region.

Here, we review the various achievements of more than three decades of scientific advances on the hydrology of the Amazon basin from RS (Figure 2), and present perspectives, currently fostered by an unprecedented availability of satellite observations and the upcoming launch of dedicated hydrology satellites, such as the Surface Water and Ocean Topography (SWOT) and the NASA-ISRO SAR mission (NISAR). This work reunited experts on RS of different hydrological processes of the Amazon basin to review specific topics and discuss paths toward scientific advances as well as the opportunities shaping this field for the next decades. Reviews account for variables of the hydrological cycle such as precipitation, evapotranspiration, surface water elevation, surface water extent, floodplain and river channels topography, water quality (e.g., estimation of sediments, chlorophyll, and dissolved organic matter), total water storage and groundwater storage that is presented in separate sections (Figure 2). Each section describes how the variable is retrieved from RS observations, presents the scientific advances that have been achieved from this information, as well as various applications in the basin, and discusses future challenges. Then, four sections are dedicated to the integration of RS data in the fields of water budget closure, hydrological and hydraulic modeling, aquatic environments, and environmental changes over the Amazon. Section 7 summarizes the scientific advances, the knowledge gaps, and the research opportunities regarding Amazon hydrology and ecosystems, including the forthcoming satellite missions. It also presents how the lessons learned from Amazon experiences are benefiting other large river basins worldwide. The two final parts discuss how to move forward from the scientific advances toward basin-scale water resources planning and new environment monitoring tools, and highlight our recommendations that set forward the research agenda of Amazon hydrology from space for the coming decade.

2. Precipitation

Precipitation is a crucial component of the water cycle (Bookhagen & Strecker, 2008; Espinoza Villar, Ronchail, et al., 2009; Salati & Vose, 1984; Trenberth, 2011), characterized by high spatial and temporal variability. In the Amazon basin, precipitation is related to complex interactions of various large-scale physical and dynamic processes as well as local features, which are responsible for the temporal and spatial distribution of precipitation (Figueroa & Nobre, 1990). For instance, in addition to the orographic rains that occur in the transition between the Andes mountains and the Amazon, the substantial transpiration from the forest contributes to abundant water fluxes to the atmosphere, which eventually returns to the land as recycled precipitation and contributes up to around 30% of the basin's rainfall (Bosilovich & Chern, 2006; Eltahir & Bras, 1994; Fisher et al., 2009; Salati & Nobre, 1991; Staal et al., 2018; Van Der Ent et al., 2010; Yang & Dominguez, 2019; Zemp et al., 2014). This contribution is normally presented as a convection process, which helps to maintain a climatological upper-level, large-scale circulation known as the Bolivian high (Lenters & Cook, 1997; Virji, 1981), and together with other related precipitation patterns are affected by both global-scale phenomena (e.g., El Niño-Southern Oscillation [ENSO], Tropical Atlantic sea surface temperature [SSTemp]) and local forcing, such as land cover structures (Aceituno, 1988; Gutierrez-Cori et al., 2021; Koren et al., 2008; Leite-Filho et al., 2020; Lin et al., 2006).

Mainly because of its large extent, precipitation regimes in the basin differ from one region to another in terms of the seasonal pattern (Figures 3c–3f), and on a more local scale, rainfall regimes are highly variable in space (Arias et al., 2021; Espinoza et al., 2009). Therefore, accurate and reliable rainfall measurements are crucial for the study of climate trends and variability, and also for the management of water resources and weather, climate, and hydrological forecasting in this region (Jiang et al., 2012; Liu et al., 2017; Yilmaz et al., 2005).

Gauge observations are traditionally used to measure precipitation directly at the land surface (Kidd, 2001), and various large-scale data sets at different scales have been developed from these in situ observations (Becker et al., 2013; Kidd et al., 2017). However, in situ measurements have several drawbacks, such as incomplete cover over sparsely populated areas, a common feature of Amazonian countries, or in remote regions at high altitudes in the Andes (Condom et al., 2020). In addition, the variability of rainfall means that the measurements from in situ stations are typically not representative of the surrounding areas, or maybe inaccurate (Kidd et al., 2017; Prabhakara et al., 1986). In the Amazon basin, for instance, rainfall stations are typically located in the cities, placed near to the main tributaries, and low density of stations is observed in tropical forests and in regions not accessible. Therefore, the low density of the rain gauge network and the lack of homogeneity in the time series prevent reliable monitoring using ground data (Debortoli et al., 2015; Delahaye et al., 2015; Espinoza Villar, Ronchail, et al., 2009; Ronchail et al., 2002). Collecting complementary observations to in situ measurements is then fundamental to obtain an estimation of rainfall over the continent's surfaces (Kidd & Levizzani, 2011; Van Dijk & Renzullo, 2011; Wanders et al., 2014).

Satellite observations of precipitation have become available on a global scale in recent decades. These satellites mainly use infrared (IR) and microwave (MW) sensors to provide precipitation estimates using different techniques (Kidd & Huffman, 2011). The sensors used to estimate precipitation can be classified in three categories (Prigent, 2010): (a) visible/IR (VIS/IR) sensors on geostationary (GEO) and low Earth orbit (LEO) satellites, (b) passive MW (PMW) sensors on LEO satellites, and (c) active MW (AMW) sensors on LEO satellites. Imaging systems on GEO provide the rapid temporal update cycle needed to capture the

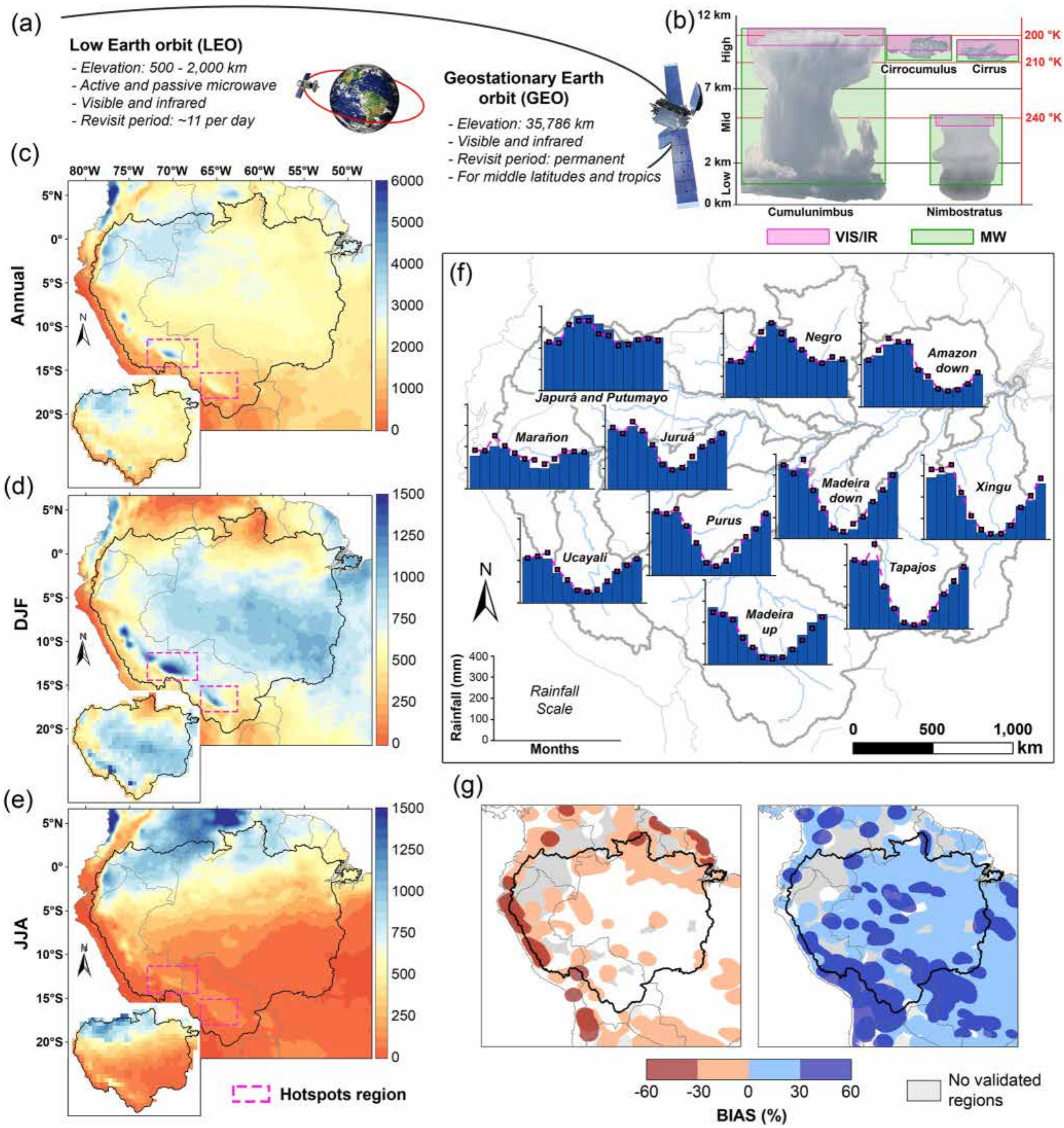

Figure 3. (a) Schematic representation of remote sensors for precipitation estimation onboard satellites. (b) Illustration of the VIS/IR and microwave coverage range for different cloud types. Precipitation climatology for (c) Annual, (d) Austral summer (DJF), and (e) Austral winter (JJA) from CHIRP v2 data set (1981–2020) at 5 km spatial resolution and HOP data set (1981–2009) (Espinoza et al., 2016; Guimberteau et al., 2012) in small boxes at left-bottom at ~100 km spatial resolution. (f) The annual regime for 11 large basins of the Amazon, based on HOP data sets (1981–2009) (bars) and the CHIRP based (1981–2020) in magenta lines. (g) Annual average negative (red scale) and positive (blue scale) bias of six precipitation RS-based and non-gauged-corrected products in the Amazon basin for the period 2000–2016, adapted from (Beck, Vergopolan, et al., 2017).

growth and decay of precipitating cloud systems on a scale of several kilometers. Current systems provide rapid hourly updates in the VIS and IR spectrum, and for optically thick clouds the precipitation can be inferred from the energy reflected by the clouds and the temperature of the cloud top, respectively. MW-based imagers on board LEO satellites are better suited than IR sensors for quantitative measurements of precipitation due to the well-established physical connection between the upwelling radiation and the underlying cloud precipitation structure (Turk et al., 2000; Figures 3a and 3b).

From these sensors, a diverse range of retrieval algorithms has been developed to estimate precipitation, which requires careful validation and provides information about their quality, limitations, and associated uncertainties. These algorithms are mainly divided into the so-called "microwave-calibrated" and "morphing" methods (Huffman et al., 2007; Joyce et al., 2004; Kidd et al., 2003; Marzano et al., 2004; Paola et al., 2012). However, there are differences among these data sets due to shortcomings in the sources and in the generation of the products. Therefore, LEO MW, GEO VIS/IR, gauge-based, and reanalysis data have been blended together to take advantage of the inherent relative benefits of each type of sensor and product (Figure 3a). This can increase accuracy, coverage, spatial-temporal resolution, spatial homogeneity, and temporal continuity (Adler et al., 1994; Huffman et al., 1995; Joyce et al., 2004; Levizzani et al., 2007; Sorooshian et al., 2002; Tapiador et al., 2004; Vicente et al., 1998; Xie et al., 2003).

In terms of operationally available data sets, these include the Tropical Rainfall Measuring Mission (TRMM; Huffman et al., 2007), the Climate Hazards Group InfraRed Precipitation (CHIRP; Funk et al., 2015), the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Ashouri et al., 2015), Integrated Multi-satellite Retrievals for GPM (IMERG; Huffman, Bolvin, & Nelkin, 2015; Huffman, Bolvin, Braithwaite, et al., 2015), Multi-Source Weighted-Ensemble Precipitation near-real-time (MSWEP-NRT; Beck et al., 2018) and the Climate Prediction Center (CPC) morphing technique (CMORPH; Joyce et al., 2004) products, among others. Although an increasing number of precipitation data sets with higher spatial and temporal resolution has been constructed and compared directly or through the application of hydrological models, uncertainty and inconsistency are found among the different data sets (Beck et al., 2018; Beck, Vergopolan, et al., 2017; Collischonn et al., 2008; Correa et al., 2017; Sun et al., 2018; Tapiador et al., 2017). A summary of satellite-derived rainfall data sets currently available for the Amazon region is provided in Table 1.

Precipitation information based on RS has contributed substantially in the last decades to the understanding of key processes causing spatial and temporal variability of precipitation, as well as local and regional atmospheric processes related to precipitations. These global or quasi global data sets generally provide records of precipitation suitable for the climate and hydrological studies, such as hydrological reanalysis initiatives evaluated in the Amazon on regional (e.g., Correa et al., 2017; Wongchuig et al., 2019) and global scales (e.g., Balsamo et al., 2015; Rodell et al., 2004; Van Huijgevoort et al., 2013). For instance, many studies have used satellite rainfall databases to force hydrological models. One of the first studies was done in the Tapajós River basin, one of the major tributaries of the Amazon basin, using TRMM precipitation estimates as input to a precipitation-runoff model (Collischonn et al., 2008). In order to represent the interannual, intraseasonal (30–70 days, Kiladis & Mo, 1998) and multidecadal series in the Amazon, different research has been evaluated (Correa et al., 2017). Satellite-based data sets were also used in water balance approaches to evaluate long-term trends (Espinoza, Ronchail, et al., 2019; Heerspink et al., 2020; Pacada et al., 2020; X. Y. Wang et al., 2018) and monthly variations of runoff (Builes-Jaramillo & Poveda, 2018). In addition, hydrological extreme events have been reported in the Amazon basin during the last decades, which has been possible by using satellite-based rainfall estimates (Barichivich et al., 2018; Espinoza et al., 2012, 2014; Funatsu et al., 2021; Gloor et al., 2013; Marengo & Espinoza, 2016; Satyamurty, da Costa, Manzi, & Candido, 2013; Sena et al., 2012). Applications of precipitation databases to the understanding of the hydrologic cycle through modeling are described in Section 6.2.

However, due to inconsistencies between different databases, several evaluations of rainfall data sets were performed that consider the Amazon basin, from global evaluations (e.g., Beck et al., 2018, Beck, Van Dijk, et al., 2017; Beck, Vergopolan, et al., 2017; Sun et al., 2018), only Amazon (e.g., Cavalcante et al., 2020; Correa et al., 2017; Espinoza, Ronchail, et al., 2019; Haghtalab et al., 2020; Mayta et al., 2019; Pacada et al., 2019; Zubieta et al., 2019) and in particular regions of Amazon (e.g., Avila-Diaz et al., 2020; Bookhagen & Strecker, 2008; Chavez & Takahashi, 2017; Espinoza et al., 2015; Getirana et al., 2011; Killeen et al., 2007; Manz

Table 1
Missions and Products That Provide Rainfall Estimates Derived From Remote Sensing Data, Including Temporal-Spatial Resolution, Data Record, Satellites Used, Algorithm Retrieval and Repository Links (NRT—Near Real Time)

Name	Extended name	Satellite adjusted with	Coverage	Spatial resolution	Temporal resolution	Temporal coverage	Reference/Link
CMORPH v1.0	CPC MORPHing technique (CMORPH) V1.0	–	60°N/S	0.07°	30 min	1998–NRT	Joyce et al. (2004); Joyce and Xie (2011); Xie et al. (2017); www.cpc.ncep.noaa.gov; https://rda.ucar.edu/datasets/ds502.2; ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/CRT/
CMORPH-CRT v1.0	CPC MORPHing technique (CMORPH) bias corrected (CRT) V1.0	Gauge	60°N/S	0.07°	30 min	1998–2019	
GSMaP-Std v6	Global Satellite Mapping of Precipitation (GSMaP) Moving Vector with Kalman MVK) Standard V6	–	60° N/S	0.1°	Hourly	2000-NRT	Ushio et al. (2009); http://sharaku.eorc.jaxa.jp/GSMaP/
GSMaP-Std Gauge v7	Global Satellite Mapping of Precipitation (GSMaP) Moving Vector with Kalman (MVK) Standard gauge-corrected V7	Gauge	60°N/S	0.1°	Hourly	2000–NRT	
IMERGHHE v06	Integrated Multi-satellitE Retrievals for GPM (IMERG) early run V06	–	Global	0.1°	30 min	2010-NRT	Huffman, Bolvin, and Nelkin (2015); Huffman, Bolvin, Braithwaite, et al. (2015); Tan et al. (2019); https://gpm1.gesdisc.eosdis.nasa.gov/data/GPM_L3/GPM_3IMERGHHE.06/; https://gpm1.gesdisc.eosdis.nasa.gov/data/GPM_L3/GPM_3IMERGDF.06/
IMERGDF v06	Integrated Multi-satellitE Retrievals for GPM (IMERG) final run V06	Gauge	Global	0.1°	Daily	06/2000–present	
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)	–	60°N/S	0.25°	Hourly	03/2000-NRT	Ashouri et al. (2015); Nguyen et al. (2019); Sorooshian et al., 2000); https://chrsdata.eng.uci.edu/
PERSIANN-CCS	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) Cloud Classification System (CCS)	–	60°N/S	0.04°	Hourly	01/2003-NRT	

Table 1
Continued

Name	Extended name	Satellite adjusted with	Coverage	Spatial resolution	Temporal resolution	Temporal coverage	Reference/Link
PERSIANN CDR v1R1	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) Climate Data Record (CDR) V1R1	Gauge	60°N/S	0.25°	Daily	1983–present	
SM2RAIN-CCI v2	Rainfall inferred from European Space Agency's Climate Change Initiative (CCI) satellite near-surface soil moisture V2	Soil Moisture	Quasi Global/Land	0.25°	Daily	01/1998–12/2015	Brocca et al. (2014); Ciabatta et al. (2018); https://zenodo.org/record/846260; https://doi.org/10.5281/zenodo.846259
SM2RAIN-ASCAT v1.2	Rainfall inferred from Advanced SCATterometer soil moisture	Soil Moisture	Global	12.5 km	Daily	2007–2019	Brocca et al. (2019); https://doi.org/10.5281/zenodo.3635932
GPM + SM2RAIN v0.1	Rainfall inferred from ASCAT H113 H-SAF, SMOS L3 and SMAP L3 soil moisture	Soil Moisture	Global	0.25°	Daily	2007–2018	Massari (2020); https://doi.org/10.5281/zenodo.3854817
TMPA-3B42RT v7	TRMM Multi-satellite Precipitation Analysis (TMPA) 3B42RT V7	–	60°N/S	0.25°	3-hr	03/2000-NRT	Huffman et al. (2007); https://disc.gsfc.nasa.gov/datasets/TRMM_3B42RT_7/summary; https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_7/summary
TMPA-3B42 v7	TRMM Multi-satellite Precipitation Analysis (TMPA) 3B42 V7	Gauge	50° N/S	0.25°	3-hourly	12/1997–01/2020	
TMPA-3B43 v7	TRMM Multi-satellite Precipitation Analysis (TMPA) 3B43 V7	Gauge	50°N–50°S	0.25°	Monthly	1998–2020	Huffman et al. (2010); https://disc2.gesdisc.eosdis.nasa.gov/data/TRMM_L3/TRMM_3B43.7/
GridSat v1.0	P derived from the Gridded Satellite (GridSat) B1 thermal infrared archive v02r01	–	<50°	0.1°	3-hr	1983–2016	Knapp et al. (2011); https://www.ncdc.noaa.gov/gridsat/

Table 1
Continued

Name	Extended name	Satellite adjusted with	Coverage	Spatial resolution	Temporal resolution	Temporal coverage	Reference/Link
ERA5 -HRES	European Center for Medium-range Weather Forecasts ReAnalysis 5 (ERA5) High RESolution (HRES)	Reanalysis	Global	0.28° (~31 Km)	Hourly	2008–NRT	Hersbach et al. (2018, 2020)
ERA5 – EDA	European Center for Medium-range Weather Forecasts ReAnalysis 5 (ERA5) Ensemble DataAssimilation (EDA) ensemble mean	Reanalysis	Global	~0.56°	Hourly	2008–NRT	
ERA5-Land	European Center for Medium-range Weather Forecasts ReAnalysis 5 (ERA5)	Reanalysis	Global	0.1°	Hourly	01/1981–present	https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land
CHIRP v2.0	Climate Hazards group InfraRed Precipitation (CHIRP) V2.0	Reanalysis	50°N/S	0.05°	Daily	1981-NRT	Funk et al. (2015); https://data.chc.ucsb.edu/products/CHIRP/daily/netcdf/; https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/
CHIRPS v2.0	Climate Hazards group InfraRed Precipitation with Stations (CHIRPS) V2.0	Gauge + Reanalysis	50° N/S	0.05°	Daily	01/1981–present	
GPCP-1DD v1.2	Global Precipitation Climatology Project (GPCP) 1-Degree Daily (1DD) Combination V1.2	Gauge	Global	1°	Daily	10/1996–11/2015	Huffman et al. (2001, 2016); https://rda.ucar.edu/datasets/ds728.3
GPCP-PEN v2.2	Global Precipitation Climatology Project (GPCP) pentad precipitation analysis (PEN)	Gauge	Global	2.5°	5-daily	01/1979–06/2017	Xie et al. (2011); https://cmr.earthdata.nasa.gov/search/concepts/C1214566485-NOAA_NCEI. http://apdrc.soest.hawaii.edu/dchart/index.html?dsetid = e53e32f2c760e6375a4de86bd4718cba
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications 2	Gauge + Reanalysis	Global	~0.5°	Hourly	1980–NRT	Gelaro et al. (2017); Reichle et al. (2017)
MSWEP v2.2	Multi-Source Weighted-Ensemble Precipitation (MSWEP) V2.2	Gauge + Reanalysis	Global	0.1°	3-hr	01/1979–NRT	Beck et al. (2019); Beck, Van Dijk, et al. (2017); www.gloh2o.org

Table 1
Continued

Name	Extended name	Satellite adjusted with	Coverage	Spatial resolution	Temporal resolution	Temporal coverage	Reference/Link
CMAP	CPC Merged Analysis of Precipitation (CMAP)	Gauge	Global	2.5°	Monthly	1979–present	Huffman et al. (1997); ftp://ftp.cpc.ncep.noaa.gov/precip/cmap/
CPC-Global	CPC Unified Gauge-Based Analysis of Global Daily Precipitation	Gauge	Global	0.5°	Daily	2006–present	Chen et al. (2008); https://ftp.cpc.ncep.noaa.gov/precip/CPC_UNI_PRCP/

et al., 2017; Paccini et al., 2018; Zulkafli et al., 2014). These data sets perform differently according to the region and the time scale analyzed, which will be described in the following subsections together with the main scientific advances that have been elucidated.

Figures 3c–3e show the cumulative rainfall for the annual, wet (DJF) and dry (JJA) period, respectively, for the Amazon basin. In these figures, the Hydro-geodynamics of the Amazon basin Observatory (HYBAM) observed precipitation data set (HOP), comprised of 752 daily rain gauge stations throughout the Amazon at 1° spatial resolution (Espinoza et al., 2016; Guimberteau et al., 2012), and the 5 km resolution CHIRP data set, a non-gauged-corrected product, have been used.

Climatological studies in the basin that consider spatial patterns began in the 1980s. For instance, the evaluation of the outgoing longwave radiation (OLR) from polar orbiting satellites (mainly from NOAA), started in 1974, have been particularly useful for routine monitoring of cloudiness and deep convection areas over the tropics with pioneering work by Gruber and Krueger (1984) and Liebmann and Smith (1996). More regional rainfall patterns were revealed in the transition between the Andes and the Amazon in the so-called "rainfall hotspots" region, where rainfall can reach values higher than 6,000 mm year^{-1}, the highest rainfall in the Amazon basin (Chavez & Takahashi, 2017; Espinoza et al., 2015; Killeen et al., 2007). This region is among the rainiest areas in the world according to the IMERG Grand Average Climatology data set that covers June 2000 to May 2019 and has the world's largest squall lines (quasi-linear convective systems; Garstang et al., 1994). Extreme vertical and horizontal structures occur due to the interactions between large-scale atmospheric circulation and massive topography that affect atmospheric convection, producing the rainfall hotspots during almost the whole year (Bookhagen & Strecker, 2008; Espinoza Villar, Guyot, et al., 2009; Killeen et al., 2007). In addition, changes in forest cover in the southern Amazon have been considered as a factor that may affect processes such as the presence of convective cells, resulting in marked spatial and temporal variability (Durieux et al., 2003; Funatsu et al., 2012; Laurance & Bruce Williamson, 2001; Staal et al., 2020).

Figure 3f shows the spatial distribution of the annual cycle of precipitation based on the CHIRP and HOP data sets. Annual cycles of precipitation over the basin vary significantly, mainly related to latitude, orography, and the influence of the large-scale atmospheric features (e.g., Intertropical Convergence Zone [ITCZ], South American Monsoon System [SAMS], South Atlantic convergence zone [SACZ]; Espinoza Villar, Ronchail, et al., 2009). The bias performance of the data sets is shown in Figure 3g, which considers six non-gauged-corrected data sets (PERSIANN-CCS, MSWEP-ng v2, CHIRP v2.0, CMORPH v1.0, SM2RAIN-ASCAT, and TMPA 3B42RT v7, adapted from Beck, Vergopolan, et al., 2017). The bias of total annual rainfall for the period 2000–2016 is plotted for negative and positive values, where at least one of these databases has detected an equal or greater value of bias. These satellite data sets were validated for the Amazon basin against global and local in situ stations (e.g., GHCN, the Global Summary of the Day [GSOD] database, the Latin American Climate Assessment & Dataset). The evaluation of these data sets showed large biases in the occidental and southern Amazon, covered by the Andean headwaters.

Over the Andes-Amazon transition region, RS rainfall data have contributed to understanding the main orographic processes related to anabatic and katabatic winds, which are essential to explain the diurnal cycle of precipitation in this region (Junquas et al., 2018). In this specific region, the bias patterns of the data sets are in agreement with other research (Chavez & Takahashi, 2017; Espinoza et al., 2015) only in the Peruvian rainfall hotspots, which underestimated total annual precipitation by about 35%–40% from the TRMM-PR data set for the period 1998–2012. The general bias in some Andes regions can be explained, in part, by the predominance of cirrus clouds (confused by satellites sensors with convective clouds such as cumulonimbus that have similar cloud top temperature (Paredes Trejo et al., 2016; Thiemig et al., 2013, Figure 3b), what occurs, for instance, over the east of the southern Andes mountains (Altiplano Plateau, which extends between 15° and 22°S). This mainly happens during the wet austral summer (Barahona et al., 2017; Dinku et al., 2011; Viale et al., 2019), and where these cloud formations are orographically dependent (Chavez & Takahashi, 2017; Giovannettone & Barros, 2009; Junquas et al., 2018; Saavedra et al., 2020; Satgé et al., 2016, 2017).

Mesoscale circulation between the land surface and large water bodies in the Amazon basin produces river and coastal breeze. These systems affect the moisture transport and the spatial rainfall pattern at a local scale (Fitzjarrald et al., 2008; Santos et al., 2019; Silva Dias et al., 2004). RS data helped to reveal that river breezes reduced rainfall over the Amazon water bodies (rivers and large reservoirs) through the use of TRMM (Paiva, Collischonn, & Tucci, 2011).

Changes in land cover can produce complex mesoscale circulation patterns, including the so-called "deforestation breeze" that can happen over small deforested patches but loses strength at deforestation scales of around 100 km (Lawrence & Vandecar, 2015; Saad et al., 2010). These deforestation-induced circulation patterns can significantly alter rainfall trends at different scales (Leite-Filho et al., 2021). Rainfall patterns can also be affected from local to continental scales, with such changes being observed over the Amazon in recent decades (Butt et al., 2011; Khanna et al., 2017; Leite-Filho et al., 2019). The effects of deforestation on rainfall will be further discussed in Section 6.4.

Remotely sensed data have been used to evaluate the temporal variability on different time scales. For instance, spatial synoptic changes in rainfall patterns were evaluated using RS information due to the heterogeneous spatial distribution of weather stations and inconsistent temporal measurements of gauge data (Arvor et al., 2017; Silva Junior et al., 2018). Other studies on a daily scale focused on evaluating the performance of the TMPA V7, TMPA RT, CMORPH, and PERSIANN data sets to represent the precipitation concentration index during the period 2001–2009 (Zubieta et al., 2019). This index is an indicator for temporal precipitation distribution. The authors concluded that the best products (CMORPH and TMPA V7) can be an alternative source of data to detect changes in daily precipitation concentration during dry or wet seasons in regions of the basin that experience extreme events.

Considering that one of the main characteristics of convection processes in tropical regions is their strong relationship with the diurnal cycle (Duvel & Kandel, 1985; Minnis & Harrison, 1984), pioneer studies were performed since the 1990s for the understanding of convective patterns in the Amazon basin. Based on 9 years (1983–1991) of data from GEO IR satellites (i.e., the B3 ISCCP product) with 3-hr temporal resolution, Garreaud and Wallace (1997) documented several features of the diurnal march of the frequency of convective cloudiness. Data from SSM/I onboard the Defense Meteorological Satellite Program via application of the Goddard Profiling algorithm were also used to characterize the climatology (10-year) and the diurnal variability (6-year) of the rainfall in the basin (Negri et al., 2000). Oliveira et al. (2016) evaluated two GPM products in order to reproduce the diurnal cycle of precipitation in the central Amazon and obtained similar results to Angelis et al. (2004), who showed that rain tends to occur mainly during the afternoon in the central Amazon basin.

Rainfall information from RS has helped to identify the time of wet season beginning and ending (Wright et al., 2017), which is especially important because the prolongation of the dry season increases the vulnerability of local ecosystems and agriculture to drought and fire events (Arias et al., 2015; Fu et al., 2013; Marengo et al., 2011). One of the first RS-based assessments found that the onset of the Amazon wet season typically occurs within a single month (Horel et al., 1989). Negri et al. (1994) produced a regional precipitation climatology over the Amazon during the wet season (January–May) using three years of the twice daily Special Sensor Microwave/Imager (SSM/I) data. Changes in the seasonal cycle amplitude were also observed with the TRMM data (Liang et al., 2020).

RS information supported important developments in the understanding of the processes governing the seasonality of rainfall in the Amazon basin. The availability of satellite-derived precipitation, OLR, and reanalysis allowed the description of the thermally-driven seasonal patterns that form the SAMS, which was previously not understood as a monsoon partly because it lacks the classical seasonal inversion of absolute zonal winds (Zhou & Lau, 1998). An uncommon characteristic of the monsoon over the Amazon elucidated by these RS products is that the onset of rains occurs before the southward migration of the ITCZ and that the Bolivian high-pressure zone characteristic of the SAMS is partly generated by the latent heat release from precipitation over the basin before the traditional monsoon onset (Fu et al., 1999).

At seasonal to intraseasonal scales, OLR data from NOAA polar-orbiting satellites was used to identify the intensity and spatial features of the SACZ in the Brazilian Amazon region (L. M. V. Carvalho et al., 2004). The SACZ is a northwest-southwest convection band that extends from the Amazon basin to the southeastern Atlantic Ocean, and its intensity and geographical distribution are associated with extreme rainfall events in the southern Amazon. At the intraseasonal scale, the large-scale Madden-Julian oscillation (MJO;

Madden & Julian, 1994) has been established as the dominant mode of variability across the tropics, modulating the SACZ and other climatological features over the basin. Mayta et al. (2019) and Vera et al. (2018) used OLR data as a proxy of convection to analyze the intraseasonal variability of precipitation in South America, and, in particular, De Souza and Ambrizzi (2006) showed that the MJO is the main atmospheric mechanism of rainfall variability on intraseasonal timescales over the eastern Amazon during the wet season, which was confirmed through the use of rain gauge network by Mayta et al. (2019). Moreover, RS information has contributed to understanding the mechanisms of atmospheric circulation and rainfall data sets' performance of seasonal and intraseasonal precipitation data sets. For instance, in the Andes-Amazon transition region, particular atmospheric circulation patterns (CP) were described by Paccini et al. (2018), where particular meteorological situations are related to regional rainfall anomalies by using TRMM 3B42, TRMM 2A25 RP, and CHIRPS data sets.

Changes in the spatial and temporal distribution of rainfall in the Amazon basin may provide an indicator of climate variability and in turn are an indicator of hydrological variability, including extreme events, such as floods and droughts (e.g., Lewis et al., 2011; Marengo & Espinoza, 2016). Direct evaluation of these data sets have been done to assess the temporal evolution of rainfall through analysis of occurrence indexes such as the dry-day frequency and the wet-day frequency through the CHIRPS data set (Espinoza, Ronchail, et al., 2019); or the assessment of the trend in the length of the wet season in southern Amazon with the PERSIANN-CDR data set (Arvor et al., 2017). The interannual evolution of the hydrological processes, such as runoff coefficient, was evaluated through a water balance analysis by using the CHIRPS data set (Espinoza, Sörensson, et al., 2019). A similar approach, the long-term surface water balance over the Andes-Amazonia system, was performed by Builes-Jaramillo and Poveda (2018) through the use of in situ (precipitation from GPCC and runoff from HYBAM) and RS-based information (evapotranspiration from ORCHIDEE, GLEAM, MPI, and MOD16), which pointed out that failures and scarcity of information in the high Andes induce uncertainties and errors in the water budget. In addition, CHIRPS v2.0 was used to analyze precipitation anomalies for the identification of spatial patterns of drought over the basin related to the tropical Atlantic and Pacific SSTemp anomalies and different ENSO events (Jimenez et al., 2019).

Rainfall estimations by RS since the 1980s in the Amazon basin have depicted more amounts of rain in the north, particularly during the wet season (Espinoza, Ronchail, et al., 2019; Pacada et al., 2020; G. Wang et al., 2018) and lower amounts in the south, particularly during the dry season (Espinoza, Ronchail, et al., 2019; Leite-Filho et al., 2019). This north-south contrasting pattern is translated to the hydrological behavior of the main basins that show an intensification of the hydrological regime in the main course of the Amazon (Barichivich et al., 2018; Espinoza Villar, Guyot, et al., 2009; Heerspink et al., 2020).

Amazon characteristics pose unique challenges to satellite rainfall retrieval algorithms, both from IR and MW sensors, considering the contrast in terms of orography, climate, and changes in vegetative cover. For IR, challenges occur mainly for warm orographic rains (shown north of 10°S), where fixed brightness temperature thresholds (cooler than warm orographic clouds) tend to underestimate rainfall amounts. This would be happening in the hot-spots regions in the Peruvian and Bolivian Andes-Amazon transition (Espinoza et al., 2015). For the MW algorithms, rain overestimation comes from cold surfaces and ice over mountain tops which can be interpreted as precipitation (Dinku et al., 2011; Toté et al., 2015).

Since satellite-based rainfall estimates are adjusted based on observations from rain gauges, the accuracy of estimated rainfall values can be increased. However, this requires a network of rain gauges with adequate spatial coverage in key areas of the Amazonia and high-quality records for proper calibration and validation. In the case of in situ stations, some aspects should be considered, for instance, that rainfall estimates are likely to be biased by river breeze at some times of the year, as meteorological stations are usually located near large rivers and close to most cities (Paiva, Buarque, et al., 2011; Santos et al., 2019; Silva Dias et al., 2004).

Current satellite-borne radar missions, such as TRMM Precipitation Radar, CloudSat's Cloud Profiling Radar, or GPM Dual frequency Precipitation Radar, have low temporal resolution, therefore are unable to observe the short-time evolution of weather processes. To overcome this limitation, using only radars on LEO, it is necessary to have a constellation of them. In recent years nanosatellites (e.g., SmallSat or CubeSat platforms) have the capability to miniaturize, reduce cost and simultaneously preserve the fundamental requirements of their larger and more expensive peers. In this sense, RainCube is a potential technology demonstration mission to enable precipitation radar technologies on a low-cost platform (Peral et al., 2019).

Ground-based radars can measure the vertical structure of rain since its structure depends on the type of rain, but with better temporal resolution than MW on board satellites (Kumar et al., 2020). A recent example is the operational algorithm RAdar INfrared Blending algorithm for Operational Weather monitoring, which merges ground radar network with VIS and IR images from satellites to provide rainfall patterns and intensity over Italy (Adderio et al., 2020). New methods have emerged that take advantage of the global cell phone network and its density to estimate rainfall intensities, mainly in urban areas, but which can also be used in regions with high topographical variability (Gosset et al., 2016; Overeem et al., 2013, 2016; van het Schip et al., 2017), however, they have not yet been explored in the Amazon basin. In general, monthly and annual data sets are useful because they have an adequate agreement to the observations, but not with daily and much less sub-daily data.

3. Evapotranspiration

Evapotranspiration (ET) has considerable importance for the terrestrial climate system, providing moisture to the atmosphere, linking the water, energy, and carbon cycles (Fisher et al., 2017; M. Jung et al., 2010), and driving precipitation and temperature at local and regional scales (Marengo et al., 2018). Studies have shown that around half of the precipitation in the Amazon basin is recycled by locals ET (Salati et al., 1979; Satyamurty, da Costa, & Manzi, 2013; Zemp et al., 2017). In addition, Amazon ET constitutes an important source of moisture for southeastern South America through atmospheric low-level (often referred to as "flying rivers"), providing around 70% of the precipitation in this region (Van Der Ent et al., 2010; Pearce, 2020). Especially during the dry season, Amazon ET seems to be more efficiently converted to precipitation in the La Plata River Basin than local ET (Martinez & Dominguez, 2014).

With the advent of satellite observations, ET has been estimated at multiple spatial and temporal scales. RS models to estimate ET can be divided into two main approaches: one based on surface energy balance (SEB) and another using physical equations. One well-known energy balance model is the Surface Energy Balance Algorithm for Land (SEBAL), proposed by Bastiaanssen (1995) to overcome most of the problems of the early surface energy balance models, which were suitable only for local scale due to their dependence on local measurements for calibration. Based on principles and methods adopted in SEBAL, Allen et al. (2007) proposed the Mapping evapotranspiration at high Resolution with Internalized Calibration (METRIC) algorithm, including an internal calibration using Inverse Modeling at Extreme Conditions (CIMEC) and micrometeorological measurements to reduce computational biases inherent to energy models that use RS data (Allen et al., 2007, 2011). Other surface energy balance models were also proposed to use RS data, such as Surface Energy Balance Index (SEBI; Menenti & Choudhury, 1993), Simplified Surface Energy Balance Index (S-SEBI; Roerink et al., 2000), and Surface Energy Balance System (SEBS; Su et al., 2001).

SEB algorithms are generally defined as "One Source Surface Energy Balance" models, since they do not distinguish between soil evaporation and canopy transpiration, whereas the land surface is treated as a big leaf and as a single uniform layer (Tang et al., 2013; Zhang et al., 2016). In contrast, in the Two-Source Energy Balance (TSEB) models (Kustas & Norman, 1999; Norman et al., 1995), the soil-vegetation system is approximated as a two-layer model, where the energy fluxes are partitioned into soil and vegetation components (Norman et al., 1995). Based on the TSEB approach, the Atmosphere-Land Exchange Inverse model (ALEXI) was developed by Anderson et al. (1997), designed to represent land-atmosphere exchange over a wide range of land cover conditions. Both approaches rely on thermal RS data, using meteorological inputs as ancillary data (Zhang et al., 2016).

RS models based on physical equations are generally divided into Penman-Monteith and Priestley- Taylor equation-based approaches. Penman (1948) was the first to formulate an equation to calculate evaporation based on a physical approach using two terms, an energy term related to radiation and an aerodynamic term related to the vapor pressure deficit and wind speed (Shuttleworth, 2012). While this equation represented open water evaporation, Monteith (1965) presented an extension by adding surface and aerodynamic resistances, and thus the equation became more consistent with an estimation of ET from vegetated surfaces, resulting in the well-known Penman-Monteith equation (Monteith & Unsworth, 2013). Based on this approach, the MOD16 algorithm was formulated by Mu et al. (2007, 2011), previously proposed by Cleugh et al. (2007), to calculate ET through the integrated use of global meteorological reanalysis and RS data from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, including leaf area index (LAI), a fraction of absorbed photosynthetically active radiation (fPAR), albedo and land cover classification. Leuning et al. (2008) also proposed a similar ET algorithm based on this equation, the Penman-Monteith-Leuning (PML) using a simple biophysical model to calculate surface conductance from MODIS LAI. Another approach is the Priestley-Taylor equation (Priestley & Taylor, 1972). This model uses an empirical parameter to simplify the Penman-Monteith approach, minimizing the uncertainties related to estimating aerodynamic and surface resistances. Based on this equation, Fisher et al. (2008) developed the JPL-PT model, and Miralles et al. (2011) proposed the Global Land-Surface Evaporation Amsterdam Model (GLEAM), designed to estimate daily terrestrial evaporative fluxes and the root-zone soil moisture using maximum observations derived from RS (Martens et al., 2017). A summary of the main RS-based models to estimate ET in the South American tropics, with applications in the Amazon basin, is presented in Table 2.

RS-based ET models have improved our understanding of ET processes worldwide, allowing us to understand hydrological processes from local to large spatial and multiple temporal scales. Energy balance models have the advantage provide fine spatial resolution. These models can estimate human impacts on the energy and water cycles and on the land-surface interactions. However, since they are dependent on thermal RS data, they are generally restricted to clear-sky or cloud-free conditions, which is a major drawback, especially in tropical humid areas, such as the Amazon (Rocha et al., 2009). In addition, SEB models usually require the presence of hot and cold conditions in the satellite domain area. This requirement is a disadvantage since the selection of the hot and cold endmembers for internal calibration using the CIMEC process on RS images can generate subjective results, especially under wet regions such as the Amazon basin, where the selection of hot endmembers during both wet and dry seasons is a challenge (Khand et al., 2017). Physically-based equations have the advantage to map ET at the high temporal resolution, enabling long-term and large-scale assessments of land-surface interactions. However, some limitations include the uncertainty in parameterizing physical processes, as surface resistance and conductance, and, therefore, some models are dependent on the use of look-up tables biome-properties (Ruhoff et al., 2013). Error propagation derived from meteorological forcing data is also an issue (Gomis-Cebolla et al., 2019; Miralles et al., 2016; Panday et al., 2015; Talsma et al., 2018) since it can introduce large uncertainties in ET estimates, especially in the tropics.

In the Amazon, the spatial and temporal drivers of ET are not fully understood, and these uncertainties are reflected in how RS models estimates ET (Baker et al., 2021; Maeda et al., 2017; Sörensson & Ruscica, 2018). ET measurements have provided valuable information about seasonality and dynamics at local scales (Rocha et al., 2009). Some national initiatives, as the Brazilian National Water Resource Information System (SINGREH) and the Meteorological Database for Research from the Brazilian National Water and Sanitation Agency (ANA) and the National Institute of Meteorology (INMET), respectively, and international research projects, as the Large-Scale Biosphere-Atmosphere Experiment in Amazonia (LBA; Davidson & Artaxo, 2004), provided standardized hydrometeorological and surface flux measurements to understand energy, water, and carbon exchanges across different tropical ecosystems (Gonçalves et al., 2013; Saleska et al., 2013). However, due to the high cost of eddy covariance measurements and maintenance difficulties, there are only a few towers located across the basin, and these do not cover the whole Amazon climate-vegetation complexity. Hence, through the calibration and validation of RS-based ET models, it has been possible to extend the spatial coverage of the ET, improving our knowledge about seasonality and patterns in data-scarce areas, covering long-term assessments.

RS models have shown that ET spatial pattern (Figure 4a), seasonality (Figure 4b), and main ET drivers vary across the basin, with monthly average rates ranging from 80 mm in the southern part (including Madeira and Tapajos basin) up to 160 mm in the northern part of the basin (Negro basin). Most models, as MOD16, usually show an increase in *ET* and forest greenness as the dry season progresses in the northeastern and central Amazon, where equatorial wet areas prevail, and spatial and temporal ET seasonality is mainly driven by incident radiation and LAI (Maeda et al., 2017), corroborating with eddy covariance measurements (Christoffersen et al., 2014), despite not all models agree with this pattern (Figure 4c). For instance, while MOD16 ET seasonality is consistent with eddy covariance measurements (at K34 and K83), with higher

Table 2
Summary of the Main RS-Based Models to Estimate ET, With Applications in the Amazon

Model	Physical principles	Spatial resolution	Usual RS sources	RS main drivers	Ancillary data	Model advantages	Model limitations	Reference
ALEXI (Anderson et al., 1997)	Surface Energy Balance	375 ms to 0.05°	GOES, MODIS, VIIRS	1) Thermal (land surface temperature) 2) Multi spectral data (surface reflectance)	1) Meteorolo gical (global reanalysis) 2) Surface data (land cover)	1) Energy fluxes are partitioned into soil and vegetation components 2) Represen tation of surface processes in areas with high water availability	1) High complexity for implementation 2) Require clear sky conditions 3) Require many meteorological variables	Pacada et al. (2019)
BESS (Ryu et al., 2011)	Biophysical model	1–5 km	MODIS	1) Atmosp heric data (aerosol, water vapor, cloud, atmospheric profile) 2) Surface properties (land surface temperature, land cover, LAI, albedo)	1) Meteorolo gical (global reanalysis) 2) Surface data (global climates and vegetation)	1) Global spatial coverage and public data availability 2) Entirely independent from flux tower data, 3) Moderate spatial resolution to cover large areas 4) Multiple atmospheric and land surface data used as inputs 5) Linkage between carbon and water fluxes	1) Require many data (surface RS and meteorological variables) 2) Soil moisture effect and water evaporation from rainfall intercepted by the canopy are not explicitly included in the model 3) Complex terrain and heterogeneity of land surface are not considered, 4) Uncertainties in inputs data sets and gap-filling methods can influence the results of the model.	Swann and Koven (2017)

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Table 2
Continued

Model	Physical principles	Spatial resolution	Usual RS sources	RS main drivers	Ancillary data	Model advantages	Model limitations	Reference
MOD16 (Mu et al., 2007, 2011)	Physical approach - Penman-Monteith equation	500 m to 0.05°		1) Vegetation phenology (LAI, fPAR) 2) Surface properties (land cover, albedo)	Meteorological (global reanalysis)	1) Global spatial coverage and public data availability 2) Low complexity for implementation	1) Parametrizations of surface conductance 2) Require measured data for model calibration/parameterization 3) Limitations in areas with high soil and water evaporation 4) Moderate to high meteorological inputs	Maeda et al. (2017); H. J. F. da Silva et al. (2019); Miralles et al. (2016) [a]; Baker et al., (2021); Baker and Spracklen, (2019); de Oliveira et al. (2017); Pacada et al. (2019); Swann and Koven (2017); Vergopolan and Fisher (2016); Xu et al. (2019)
PML (Leuning et al., 2008)		500 m						Zhang et al. (2016) [a]
GLEAM (Miralles et al., 2011)	Physical approach—Priestley—Taylor equation	0.25°	AIRS, CERES, MODIS, multi-source soil moisture (ES-CCI),vegetation optical depth (VODCA)	1) Atmospheric data (radiation, precipitation, air temperature, lightning frequency) 2) surface properties (snow-water equivalent, soil moisture, vegetation cover fraction, vegetation optical depth)	Meteorological (global reanalysis)	1) Can be driven only with RS inputs 2) Moderate meteorological inputs requirements 3) Global spatial coverage and public data availability	1) Simplification of some physical processes 2) Over-dependence on water availability 3) Limitations in areas with high soil and water evaporation 4) Low spatial resolution	Miralles et al. (2016) [a]; Pacada et al. (2019); Wu et al. (2020); Baker and Spracklen, (2019); Baker et al., (2021)

Table 2
Continued

Model	Physical principles	Spatial resolution	Usual RS sources	RS main drivers	Ancillary data	Model advantages	Model limitations	Reference
PT-JPL (Fisher et al., 2008)		1°	AVHRR, MODIS	Vegetation phenology (NDVI, SAVI)	Meteorological (global reanalysis) and Satellite land surface climatology	1) Global spatial coverage and public data availability 2) Can be driven only with RS data 3) Moderate meteorological inputs requirements	1) Simplification of some physical processes 2) Many ecophysiological parameterizations 3) Limitations in areas with high soil and water evaporation 4) Low spatial resolution	Fisher et al. (2009); Miralles et al. (2016) [a]
METRIC (R. G. Allen et al., 2007)	Surface Energy Balance	30 m to 1 km	MODIS, Landsat	1) Thermal (land surface temperature) 2) multispectral data (surface reflectance)	Meteorological (from ground measurements to global meteorology)	1) Applications for regional scale in moderate to high spatial resolution 2) Less surface parameterization 3) Useful to evaluate land cover changes impacts 4) Low meteorological inputs requirements (SEBAL) 5) Higher accuracy in areas with ground measurements available (METRIC)	1) Require clear sky conditions 2) There is no distinction between soil evaporation and canopy transpiration 3) Require the presence of hot and cold extreme conditions on the domain area 4) Domain-area dependence, with limitations for large-scale applications 5) Moderate to high meteorological inputs requirements (METRIC) 6) Higher uncertainty in data scarce areas (METRIC)	Khand et al. (2017); Nóbrega et al. (2017); Numata et al. (2017)
SEBAL (Bastiaanssen, 1995)			AVHRR, MODIS, Landsat, ASTER					Nóbrega et al. (2017); Laipelt et al., (2020); de Oliveira et al. (2019)

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Table 2
Continued

Model	Physical principles	Spatial resolution	Usual RS sources	RS main drivers	Ancillary data	Model advantages	Model limitations	Reference
SEBS (Su et al., 2001)			MODIS, Landsat			1) Accuracy related to land surface temperature 2) Low requirement for meteorological inputs	1) High requirement for surface parameterization 2) Moderate to high complexity for implementation	Pacada et al. (2019)
SSEBop (Senay et al., 2013)	Simplified surface energy balance					1) Low complexity for implementation 2) Global spatial coverage and public data availability	1) Simplified energy balance 2) Moderate to high meteorological inputs requirements (METRIC) 3) Higher uncertainty in data scarce areas	Pacada et al. (2019); Senay et al., (2020) [a]

[a]Global applications including Amazon analysis.

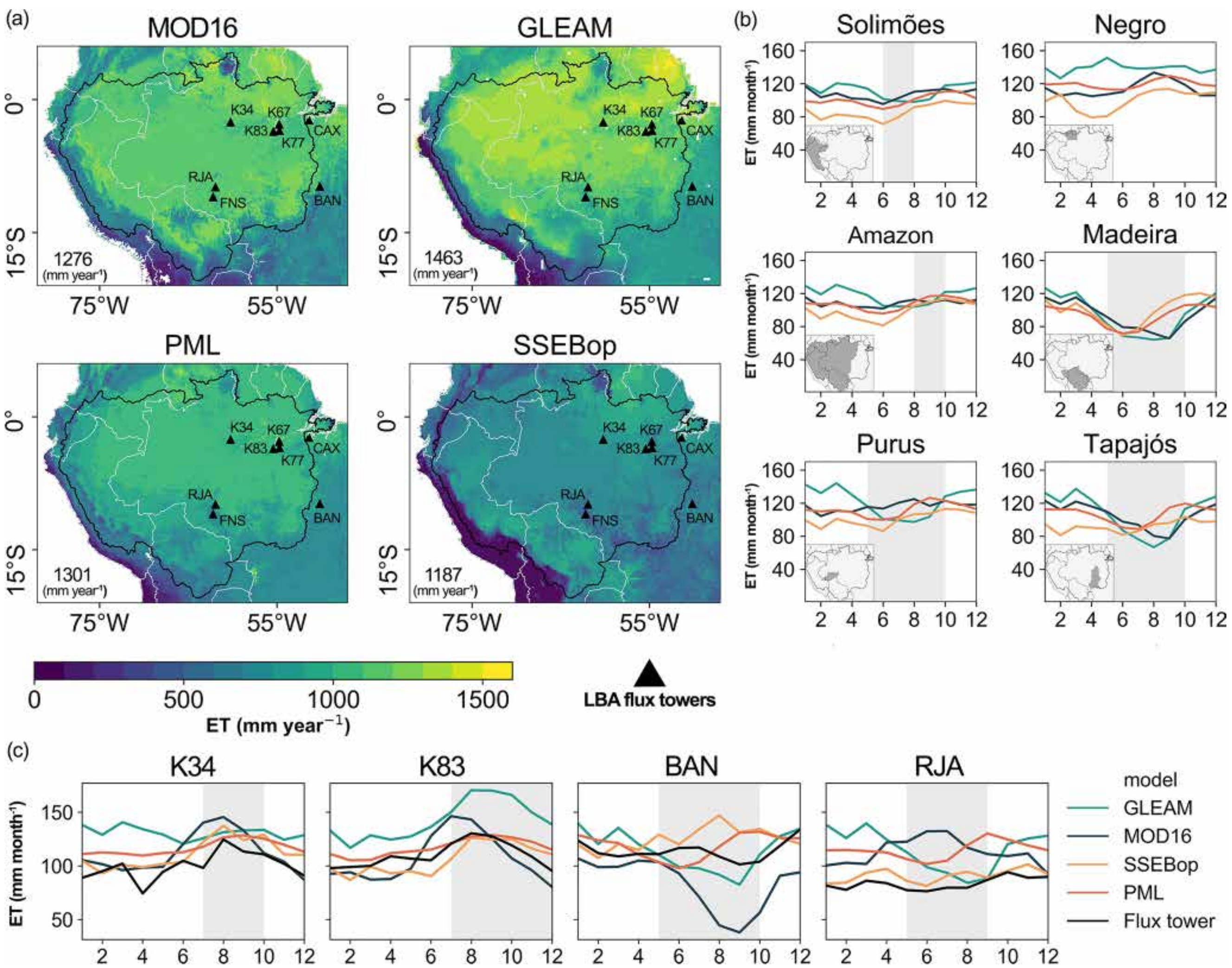

Figure 4. Spatial and temporal patterns of evapotranspiration (ET) are differently represented by RS models. (a) Spatial variability of ET annual average (2003–2017) for Global Land-Surface Evaporation Amsterdam Model , SSEBop, MOD16, and PML models; the numbers on the lower left corner of each subplot represent the annual average ET. (b) ET seasonality for major Amazon sub-basins. (c) Monthly average comparison between estimates and eddy covariance measurements from the LBA project, using data from Saleska et al. (2013). The dry season is highlighted in gray as monthly precipitation rates <100 mm month^{-1}.

rates during the dry season, seasonality of the GLEAM model (at K34), peaks during the wet season in wet regions in Amazon, since this model has a dependence on water availability, following the rainfall seasonality(Miralles et al., 2016). Furthermore, in the south and southeastern parts of the Amazon basin (at Madeira and Tapajos basin), most of the RS-based models consistently indicate a decrease ET during the dry season, following water availability (Maeda et al., 2017; H. J. F. da Silva et al., 2019). However, when RS-based models estimate are compared to eddy covariance measurements (at local scale) or water balance estimates (at large scale), the representation of the ET seasonality is still uncertain, since most of the models are unable to consistently reproduce the seasonal cycles in tropical areas, considering that multiple drivers operate simultaneously across the Amazon. Overall, in the tropics, ET seasonality is mainly regulated by water and energy availability and how vegetation assimilates both (Christoffersen et al., 2014; Restrepo-Coupe et al., 2013). Alternatively, in large data scarce areas, estimating ET using multi-model ensembles and a dense observational network across the Amazon, RS-based models can be improved through calibration and validation, helping assess model uncertainties and to understand the land surface interactions in the tropics (Gonçalves et al., 2013; Pacada et al., 2019).

While flux tower measurements have shown, at local scales, that land cover changes can impact water and energy fluxes (von Randow et al., 2004), large scale assessment with satellites based on both energy balance and physical-based equations driven by vegetation phenology and meteorological reanalysis have reinforced these findings (Baker & Spracklen, 2019; Khand et al., 2017; Laipelt et al., 2020; de Oliveira et al., 2019). All these studies demonstrated significantly lower ET rates under pasture, agricultural, and deforested areas than in primary and secondary forests (von Randow et al., 2020). These results indicate that less water returns to the atmosphere, thus affecting the precipitation recycling and contributing to changes in the dry-to-wet season, possibly making the dry season longer (Costa & Pires, 2010), while more of the precipitated water goes to runoff (Panday et al., 2015). In addition, RS-based assessments demonstrated that drought events tend to affect anthropogenic systems as pasture and agriculture areas more than primary and secondary forests, leading to an increase in air temperature, and a decrease in LAI and ET (Baker & Spracklen, 2019; de Oliveira et al., 2019). Results from MOD16 ET may assist in monitoring deforested areas in the Brazilian Amazon (H. J. F. da Silva et al., 2019). However, global remotely sensed ET, such as GLEAM, better reflect changes in vegetation greening and in air temperature increase than to deforestation, may due the lack of deforestation account in these models (Wu et al., 2020). Influence of land use changes on the water cycle will be discussed further in Section 6.4.

Our understanding about energy partitioning in the Amazon biome has improved through RS models (de Oliveira et al., 2019; Laipelt et al., 2020). For example, high resolution ET estimates using SEBAL in the south-western Amazon demonstrated significant differences among energy and water fluxes in forests and non-forest areas, such as pasture and cropland. In these anthropogenic areas, soil and sensible heat fluxes were from two to four times higher than in forested areas (de Oliveira et al., 2019). In a transitional region between Amazon and Cerrado biomes, converted areas can substantially change the energy and water fluxes, where latent heat flux is the major component in forested areas, while in deforested areas an increase in sensible heat flux is observed (Laipelt et al., 2020). These studies showed that change in land use and land cover, can significantly affect ET rates, and observed ET rates was almost two times lower in pasture than in tropical forest (Laipelt et al., 2020), and up to three times lower in non-forested areas (de Oliveira et al., 2019).

Fisher et al. (2017) summarized in 10 scientific questions the main outstanding knowledge gaps for the ET-based science. To address these questions, ET estimations need to be improved, aiming for high accuracy, high spatial and temporal scales, covering large spatial and long-term monitoring. Recent research demonstrated that RS models can estimate ET with reasonable accuracy and consistent agreement (Gomis-Cebolla et al., 2019; Martens et al., 2017; Michel et al., 2016; Zhang et al., 2019). However, for the individual ET components (soil evaporation, transpiration, and interception), they diverge considerably (Miralles et al., 2016; Talsma et al., 2018). For example, Miralles et al. (2016) showed that in tropical forests, soil evaporation is almost non-existent in GLEAM and JPL models, whereas with MOD16 this component may exceed transpiration. In the Amazon, canopy interception from JPL and MOD16 is nearly two times higher than in GLEAM model. Beyond the uncertainties related to canopy transpiration and soil evaporation, open water evaporation and ETestimation over Amazon wetlands is also a major knowledge gap. Wetland ET can be a complex process as it involves fluxes at different vegetation conditions for transpiration, evaporation from water intercepted in the canopy and from open and vegetated surface water. Changes in latent heat patterns over water bodies (rivers, wetlands, lakes and artificial reservoirs) affect the local climate circulation patterns through a breeze effect (Silva Dias et al., 2004), and have the potential to affect regional climate through precipitation suppression over the wetlands and convection initiation over wetland borders (Taylor et al., 2018).Wetland-upland differences in ET are still poorly understood over the Amazon, and only a few in situ monitoring gauges are available on floodable environments (Borma et al., 2009) that could be used for model validation. Improvements of accuracy of ET components estimates lead us to better understand ET processes, and how these components are impacted by changes in temperature, green-house gases concentration, and in the hydrologic cycle (Fisher et al., 2017; Talsma et al., 2018).

Another challenge to RS-based ETis to minimize the use of land cover parameterization to improve input model accuracy. While the performance of Penman-Monteith models can be influenced by surface conductance parameterizations to scale stomatal conductance to canopy level, Priestley-Taylor models estimates have dependence on the α coefficient. Since ET models depend on meteorological inputs, errors can also be related in both approaches by forcing data and algorithm's structure (Ershadi et al., 2015; Gomis-Cebolla et al., 2019). Moreover, measurements are still a significant limitation. In the Amazon biome, there are only eight public flux towers with data available, from the LBA project (Saleska et al., 2013), and they do not cover all vegetation and climate complexity in the Amazon basin. In addition, for surface energy balance models the main challenge, especially in the Amazon, is the requirement of clear sky conditions. However recent efforts to integrate microwave data to energy balance models are promising (Holmes et al., 2018), since microwaves are less affected by cloud cover than the thermal infrared wavelength.

RS is now supported by a range of sensors and satellites which provide thermal infrared images, and meteorological and surface observations, essential to estimate ET. In 2018 the Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) mission was launched by National Aeronautics and Space Administration (NASA) and will provide information about how vegetation responds to stress and how it uses water, focusing on vegetation temperature measurement, allowing understanding of ET dynamics and processes at a good temporal and spatial resolution (Fisher et al., 2017; Sheffield et al., 2018). Other missions will improve ET estimates and will provide valuable information to validate current models. For example, the Joint Polar Satellite System (JPSS), a mission from National Oceanic and Atmospheric Administration (NOAA) and NASA, includes a range of sensors, such as the Visible Infrared Imaging Radiometer Suite (VIIRS), that collect visible and infrared imagery, providing useful global information to monitor vegetation, and as input to retrieval hydrological variables (McCabe et al., 2017; Sheffield et al., 2018; Zhou et al., 2016). The Water Cycle Observation Mission (WCOM) from China aims to acquire consistent measurements of the water cycle components (Levizzani & Cattani, 2019; Shi et al., 2016). The FLourescence EXplorer (FLEX) mission by European Space Agency, that will map vegetation fluorescence, providing information about photosynthetic activity and vegetation stress and health, also helping to improve constraints on transpiration (Drusch et al., 2017; McCabe et al., 2017). Beyond continuity of Landsat (McCorkel et al., 2018) mission, will map long-term ET at high spatial scale, and the Gravity Recovery and Climate Experiment (GRACE) Follow-on that will bring significant opportunity to estimate ET with the water balance approach (Landerer et al., 2020).

RS has been crucial to improve our understanding of surface-atmosphere interactions through ET, despite the challenges that still exist, and these future missions are an excellent opportunity to address important scientific questions from ET-based science, allowing us to improve techniques, approaches and our knowledge about ET processes and how the impact of activities can affect the water cycle throughout the Earth, including the Amazon.

4. Surface Water

4.1. Surface Water Elevation

Surface water is a key resource for all the communities living along the Amazon River. Yet monitoring surface water elevation (SWE) and discharge in the Amazon basin is a challenge. While the basin is facing pressure on its water cycle due to human activities, the number of gauges decreased globally in the last decades (Vörösmarty et al., 2000). This threatens our capacity to understand natural and human-driven impacts of climate change on Amazonian rivers. Although, to this date, no satellite mission have been designed specifically for retrieving inland water elevations, remotely-sensed observations of SWE from radar altimetry are complementary to the historical gauge network (Fekete et al., 2012) and improve monitoring of Amazonian rivers (Calmant & Seyler, 2006; Da Silva et al., 2014).

Amazon basin has become an ideal laboratory for pioneering studies that have demonstrated the capacity of retrieving accurate SWE at particular locations from radar echoes and adapted retracking procedures. The first studies over the Amazon used observations from Seasat (Sea Satellite from NASA), launched in 1978, to derive the low water gradient of the Amazon main stem (Guzkowska et al., 1990).

The configuration of the satellite altimeter orbit defines the intersections between the satellite ground tracks and the river reaches, the so-called virtual stations (VSs), where SWE can be estimated. At a given VS, the SWE is retrieved through the inversion of the signal round-trip propagation time that provides the range. Several uncertainty corrections (due to delay in the propagation caused by the atmosphere, dynamics of Earth's surface, etc.) must be applied to this range to retrieve the SWE. Stammer and Cazenave (2017) provide an extensive discussion on SWE estimation from satellite altimetry and the associated errors. Since the first satellites, the accuracy of the orbit, which depends on the density of the atmosphere and on the resolution of the gravitational field, has improved, and is now around one centimeter (against 60 centimeters for Seasat). Yet calculating the correct range remains challenging, as it is necessary to track (on board) or retrack (on the ground) the altimetric waveform (Frappart et al., 2006; Zhang et al., 2010), using algorithms to best fit the highly variable distribution of the echo energy bounced back by the different types of surfaces in the satellite field of view (Calmant et al., 2016).

Since the first studies using Seasat data, we now have more than 30 years of monitoring of inland waters by satellite altimetry. After Seasat came GEodetic and Oceanographic SATellite (GEOSAT), that was used by Koblinsky et al. (1993) to retrieve SWE time series over the Amazon, with uncertainties ranging from 0.19 to 1.09 m compared to in situ data. The European Remote Sensing satellite (ERS-1; launched in 1991) initiated a long family of satellites that followed the same 35-day repeat orbit (ERS-1, ERS-2, ENVISAT -Environmental Satellite, and SARAL -Satellite with ARgos and ALtika), which covered the 1991–2016 period. A major advance was made by the Observations des Surfaces Continentales par Altimetrie Radar (OSCAR) project, that evaluated the ICE-2 specific retracking of radar echoes for ice caps (Legresy et al., 2005) -a re-tracker based on fitting the leading edge and the trailing edge slope of radar waveforms to a Brown function-for ERS-1, ERS-2 and ENVISAT, and promoted its delivery in the Geophysical Data Records (data files containing along-track altimeter measurements and the corrections that are needed to be applied to the range in order to retrieve WSE).

The retracking of radar echoes was analyzed by Frappart et al. (2006, 2016) and Da Silva et al. (2010) over 70 ERS-2 and ENVISAT VSs and a large range of river widths (from tens of meters to kilometers). They reported that the proper selection of the data considered as representative of the water body is as important as the choice of the retracking algorithm. The data from the 10-day repeat orbit of Topex/Poseidon (T/P) and Jason-2/3 have also been assessed in the Amazon basin. Seyler et al. (2013) highlighted the gain of Jason-2 (ranging from 2008 to 2016 on its nominal orbit) in comparison to T/P (from late 1992 to 2005), with an uncertainty around 0.35 m, possibly due to the sensor's better capacity to discriminate the surrounding floodplain from the river.

All these missions operated in low resolution mode, i.e., the footprint on ground is large (some kilometers, depending on radar operating band) and the echoes returning to the antenna are influenced by the surroundings. The SAR mode, active on Sentinel-3 satellites, allows a reduction of the surrounding contributions by slicing the disc illuminated by the echo at a given time (Raney, 1998). This reduction provides a much better along track resolution, however it does not resolve some issues such as cross-track sloping measurements (Bercher et al., 2013). The addition of a second antenna, as on Cryosat-2, allows the SAR Interferometric mode to correct these cross-track measurements, hence allowing an improvement in the accuracy of SWE time series. However, Croysat-2 is not popular for SWE monitoring over rivers since its orbit shifts around 30 km westward every 28.9 days, 7 km eastward every 89 days and comes back to the same place every 369 days. Indeed, most of the studies on the use of satellite altimetry in the Amazon basin have focused on repetitive orbits, even though some studies have explored the use of missions in drifting or long-term repetitive ones and found good accuracy for SWE monitoring (e.g., Bogning et al., 2018). As of today, main applications of drifting or long-term repetitive missions consist in constraining or calibrating hydrodynamic models, however no study has yet focused on the Amazon basin. Such missions, instead of providing a SWE observation on a 10-day or almost monthly basis with a large intertrack distance at the equator (between 60 and 100 km), provide a much denser spatial span but with observations separated from another in time. The use of ICESat (Ice, Cloud, and land Elevation Satellite) laser altimetry data was investigated by Hall et al. (2012). They concluded that this mission can be a valuable source of data for monitoring rivers from the Amazon, with accuracies of some tens of centimeters when compared to gauges. The ICESat mission was continued by ICESat-2, launched in 2018. Studies by Bercher et al. (2013) and Jiang et al. (2017) concluded that the SAR mission CryoSat-2 offers new opportunities to monitor narrow rivers in the Amazon basin, and should help linking the present and future altimetry missions.

The differential interferometry technique with SAR data allows obtaining information about changes in surface displacements, such as topographic changes. Centimeter-scale measurements of water level changes throughout inundated floodplain vegetation using interferometric SAR were obtained over the

Table 3
Data Sets of Surface Water Elevation Time Series Over the Water Bodies

Name	Producer	Weblink	Reference	Target	Delivery time
G-REALM	USDA NASA	https://ipad.fas.usda.gov/cropexplorer/global_reservoir/Default.aspx#SatelliteRadarAltimetry	Birkett et al. (2017)	Lakes and reservoirs	NTC
River & Lake	De Montfort University	http://altimetry.esa.int/riverlake/shared/main.html	Berry et al. (2005)	Rivers, Lakes and reservoirs	SCT (discontinued)
DAHITI database	German Geodetic Research Institute	https://dahiti.dgfi.tum.de/en/	Schwatke et al. (2015)	Rivers, lakes reservoirs and wetlands	NTC & reanalysis
GRRATS product	Ohio State University	https://podaac.jpl.nasa.gov/dataset/PRESWOT_HYDRO_GRRATS_L2_VIRTUAL_STATION_HEIGHTS_V2	Coss et al. (2020)	Rivers	Reanalysis only
Hidrosat	ORE-HYBAM and ANA	http://hidrosat.ana.gov.br/	Carvalho et al. (2015)	Rivers	NTC
Hydroweb	IRD/LEGOS, CNES (French Space Agency), and Universidade do Estado de Amazonas	http://hydroweb.theia-land.fr/	Crétaux et al. (2011); Da Silva et al. (2010)	Rivers, lakes and reservoirs	STC & reanalysis

Note. STC, Slow-Time Critical - delivered at maximum after 3 days; NTC, Non-Time Critical -delivered typically within 1 month.

Amazon floodplains for the first time (Alsdorf, Birkett, et al., 2001; Alsdorf, Smith, & Melack, 2001; Alsdorf et al., 2000). This estimation is possible due to the radar pulse interactions with the water surface and the trunks of flooded vegetation causing a double-bounce path (Alsdorf et al., 2000; Hess et al., 1995). Lee et al., 2020 and Mohammadimanesh et al. (2018) reviewed the methods and limitations of the technique for applications in wetlands.

To date, SWE information is available as raw data and as processed data. Some groups or institutions provide processed SWE time series (see Table 3). Each data set provides SWE on selected water bodies, all over the world or in specific regions, and have different objectives in terms of operability. Processing and filtering procedures vary between each group, and time series of the same VSs can vary from one group to another.

Figure 5 provides the location of all virtual stations in the Amazon basin from the Hydroweb website. Figure 5a is a representation of the median amplitude of SWE at each VS. Amplitude of SWE measured by the satellites is lower in the headwaters (0–3 m) and medium size rivers (3–6 m) compared to Solimões-Amazonas main stem and its tributaries (9–12 m). Largest values are found for the Purus River (>15 m), a right bank tributary. Figures 5b and 5c provide the mean month for high and low flows, respectively, indicating the influence of rainfall partition in the northern and southern parts of the basin and the gradual shift due to the flood travel time along the rivers and floodplains (~1–3 months). Figures 5d and 5e provide multi-mission SWE time series ranging from 2002 to now with ENVISAT and Sentinel3-B and from 2008 to 2020 with Jason-2 and Jason-3, respectively. It shows the strong seasonal signal of the gradual flood of the Amazon rivers, and interannual variability of maximum and minimum stages.

Owing to its relatively dense spatial cover (see Figure 5), satellite altimetry has been used for deriving the altimetric profiles of rivers throughout the basin. These profiles, computed for low and high waters for the Negro River from T/P VSs (Frappart et al., 2005) and ENVISAT VSs (Leon et al., 2006), indicated a lower slope for the Negro River over more than 500 km (from its mouth to upstream reaches) than for the Solimões River (confirmed by Callède et al., 2013). Such a difference explains the strong backwater effect that occurs in the lower section of the Negro River and alters the time of peak and low flows. Other backwater effects, mainly from the Amazon main stem on its tributaries, were evident in the river profiles from satellite altimetry. However sparse in time, satellite altimetry observations now provide a dense enough network to monitor extreme events such as those that occurred in 2005 and 2010 in the Amazon (Frappart et al., 2012; Da Silva et al., 2012).

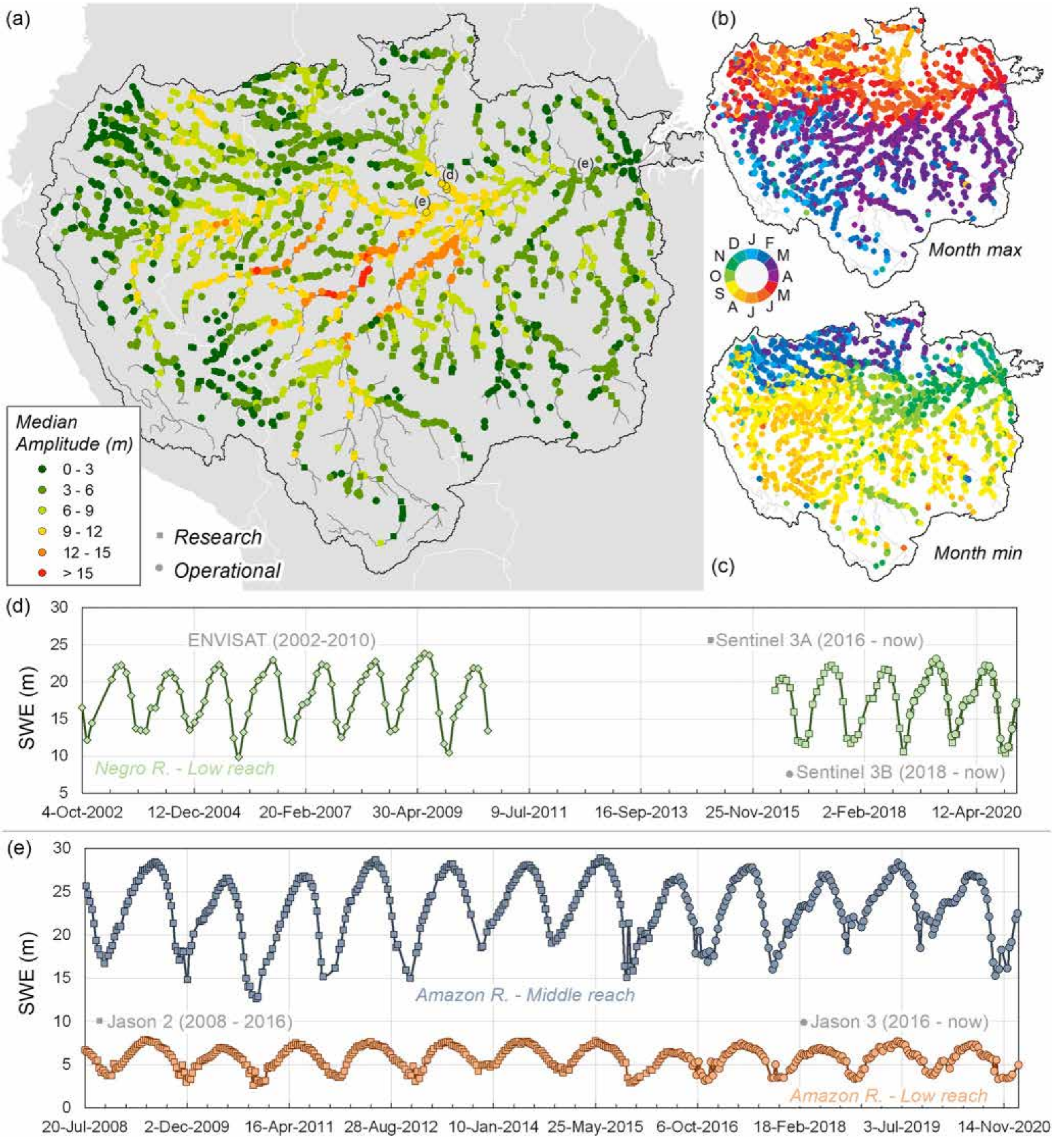

Figure 5. (a) Location of the virtual stations freely available on Theia-hydroweb (http://hydroweb.theia-land.fr/) and median amplitude of the time series. Dots are operational VSs (from currently flying missions and updated in near real time) and squares are research VSs (identified as reanalysis in table W). VSs rounded in black are drawn in (d and e; b) month of maximum surface water elevation (SWE) for the mean monthly time series at each VS; (c) Month of the minimum SWE for the mean monthly time series; (d) Composite time series of the VSs close one to each other on the lower Negro River, VSs NEGRO_KM1444, NEGRO_KM1420 and NEGRO_KM1404, (e) Time series on the Amazon middle reach and Amazon lower reach composed of Jason-2 and Jason-3 observation at VS AMAZONAS_KM1534 and AMAZONAS_KM0397, respectively.

A straightforward application of these profiles is to derive the spatiotemporal variations of the water surface slope. While former studies focused on the spatial variations of the surface water gradient, a first try to estimate the temporal variations of the Amazon main stem slope was performed in Birkett et al. (2002) using VSs from the T/P mission. They revealed changes in the sign of the rate of slope variation that were explained by the river not reaching equilibrium. Although the slopes from Birkett et al. (2002) compared well with slopes from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) - a snapshot of profiles and slopes in February 2000 (LeFavour & Alsdorf, 2005)—and with gauge data (Calmant et al., 2013), these breaks in slope variation rate were not found in profiles extracted from more recent and complet. altimetric databases (Calmant et al., 2016). Paris et al. (2016) estimated two different time series of slopes from satellite altimetry in the lower Negro River: the first was calculated using a daily interpolation of upstream and downstream SWE time series, providing a daily slope time series, and the second was calculated using the mean climatology of upstream and downstream VSs. Although the stage to discharge relationship was improved when considering the variation of slope with time estimated through both methods, it is the monthly means that provided the best improvement. This illustrates the difficulty in inferring slopes from non-daily uncertain observations.

By coupling satellite altimetry and a hydrologic and hydraulic model through stage to discharge rating curves, Paris et al. (2016) provided a map of estimated bottom of river in the entire Amazon basin using data from ENVISAT and Jason-2 missions. This map was then used by Garambois et al. (2017) on a reach of the Xingu River to parameterize a hydraulic model. Such cases where the satellite ground-track crosscuts several times the same river reach allow a more refined analysis of water surface slope. This occurs in sinuous rivers flowing from north to south (or the contrary) like the Xingu River, a right margin tributary of the Amazon River (Figure 2). Given these conditions, the authors verified that the presence of an obstacle in the river bed produces temporal changes in water surface slope observed by satellite altimetry. Brêda et al. (2019) proposed a benchmark of methods of altimetric data assimilation, ranging from direct insertion to a hydraulically based Kalman filter, to improve bathymetry estimates of the Madeira River. They concluded that satellite altimetry can be used for better constraining SWE and flood inundation simulations. An analysis of SWE from the ENVISAT mission revealed water passing from the Negro River to the Solimões River through their interconnected floodplains at high stages (Da Silva et al., 2012).

The capacity to observe channel-floodplain connectivity through altimetry was investigated by Park (2020). By observing seasonal changes in SWE in rivers and surrounding floodplains, they separated the role of channelized flows and of overbanks flows, which contributes to surface water storage and smooths the channelized-induced topography. The floodplain located between the Madre-de-Dios, the Beni, the Guapore and the Mamore rivers in the upper Maderia basin was characterized using ENVISAT and SARAL data (Ovando et al., 2018). Water level differences between the frequently flooded regions, with no direct connection to the Andes, and the regions subject to sporadic though large flood events were distinguished. Recently, Fleischmann et al. (2020) produced SWE time series in the complex Negro River interfluvial wetlands from Sentinel3-A data. For the first time, they reported <1 m water level variations in these complex areas. Their results show that satellite altimetry can help understanding the hydraulic behavior of complex ungaged areas and help validate hydrologic and hydraulics models.

Alsdorf et al. (2000, 2005, 2007) applied for the first time interferometric SAR (InSAR) in the central Amazon floodplains and showed that the water flows in the floodplains are dynamic in space and time, changing the direction with the flood wave of the river. Before the flood, the flows are controlled by the local topography and the surface water elevation in the floodplain is not equivalent to the river level (Alsdorf et al., 2007). By assuming that the water surface in the floodplain is equivalent to those in the main channel, estimates of water storage derived from flood routing can be overestimated, as shown by Alsdorf (2003). H. C. Jung et al. (2010) compared temporal changes in floodplain water in the Amazon and Congo basins. While the Amazon River is connected by many channels to the floodplains and has complex flow patterns, the Congo Rivers (and especially the Cuvette Centrale) have sparse connections with interfluvial areas and flow patterns that are not well defined and have diffuse boundaries. The patterns of water surface variations in the floodplains located on the Tapajós and Solimões rivers were examined by Wang et al. (2011) and Cao et al. (2018), respectively. The most recent SAR missions allowed monitoring of smaller water bodies.

Through direct assessment or combination with other RS products, satellite altimetry can be used to derive non-measured hydrological variables. Pfeffer et al. (2014) were able to infer the varying exchanges between surface water and the groundwater base-level from 491 ENVISAT VSs located all over the basin. Estimates of deviations from groundwater base-level reached up to 5 m. Frappart et al. (2012) made a joint use of satellite altimetry and inundation extent to derive variations of surface continental water storage (see Section 5). These two variables were used in Frappart et al. (2019) to estimate the spatiotemporal variability of groundwater storage in the Amazon basin. de Oliveira Campos et al. (2001) and Silva et al. (2019) found signatures of global climatic events such as ENSO and sea surface temperature variations in the T/P and Jason-2 SWE time series, respectively. Since the SWE estimates are now delivered in near real time, rating curves that relate SWE with discharge and depth, have been the focus of several studies (see details in Section 6.2). These rating curves were either computed using local gauges (Zakharova et al., 2006) or model outputs (Getirana et al., 2012; Leon et al., 2006). By constraining the rating curve parameters into Manning-realistic bounds, Paris et al. (2016) showed that discharges predicted from satellite altimetry are comparable to those measured in situ. The original SWE time series or their conversion into discharge offer an independent tool to validate hydrological models (Paris et al., 2016) and their rainfall inputs, and in situ data (Da Silva et al., 2014).

With its disruptive technology based on swath altimetry, almost-global coverage and joint observation of SWE, river width and slope, the SWOT mission, to be launched in 2022, will permit an unprecedented observation of SWE all along the river network and on major lakes and floodplains. As highlighted by Biancamaria et al. (2016), SWOT observation of SWE will permit a better monitoring of transboundary waters and wetlands in the Amazon. Dedicated to sample all rivers wider than 100 m and lakes larger than 250 × 250 m, the mission will permit a consequent reduction of global and regional models, noteworthy through data assimilation (Emery et al., 2020; Wongchuig et al., 2020). The estimate of discharge from altimetry will benefit from SWOT data, both thanks to the global coverage and the observation of slopes, allowing a better constraining of uncertain hydraulics (Wilson et al., 2015).

Thanks to more than 20 years of studies, EO data sets, especially satellite altimetry, have been revealed as an unprecedented tool to monitor continental watersheds and their droughts and floods (Lopez et al., 2020). The current satellite altimetry missions opened the era of operational monitoring from space at large scale, and this will be of critical importance in the coming decades in the large tropical transboundary watershed that is the Amazon basin. With almost two thousand VSs distributed all over the basin and available for free on websites, and potentially hundreds more, satellite altimetry can favorably complement the traditional in situ network, whose location usually depends on the proximity to a city or town. However, to operationally monitor non-open waters such as permanently or seasonally flooded vegetated floodplains remains challenging. In fact, few lakes and reservoirs are monitored by altimetry routinely in the basin though more could be (Crétaux et al., 2011; Crétaux & Birkett, 2006). The forthcoming missions will benefit from past research to improve the accuracy of SWE time series and promote its use for monitoring more local phenomena, such as floodplain-channel exchanges. Although limited due to availability of appropriate data, InSAR data sets help characterize floodplains/rivers connectivity and dynamics. The global coverage of the forthcoming SWOT mission will increase greatly our understanding on the global water cycle and should allow a better quantification of past and current inter-mission biases, helping turn satellite altimetry archives into a unique climatic data set and understanding the impacts of climate change and human activities on the basin. Such a task will benefit of the ongoing Validation of Altimetric Satellites for HYdrology in Brazil project (VASHYB, https://swot.jpl.nasa.gov/documents/1054/), which aims to validate SAR and InSAR observations. The SWOT mission will dramatically increase our capacity to model the Amazon basin and the variations of its water cycle, thanks to the new capacity to monitor hydrological variables (height, width, slope, and associated discharge) of hundreds of rivers 100 m wide (Biancamaria et al., 2016). The centimetric accuracy in SWE and slope (Desai, 2018) should provide new insights on water fluxes in the Amazon. Since the main limitation for a broader use of satellite altimetry remains its relatively low temporal sampling, future missions such as the SMall Altimetry Satellites for Hydrology mission (SMASH, Blumstein et al., 2019), broadcasted together with the current constellation, should help tackle this issue.

4.2. Surface Water Extent

Characterizing the extent and variation of surface water bodies and aquatic ecosystems, which include rivers, streams, lakes, wetlands, as well as seasonally inundated floodplains, forests and savannas, is of primary importance to the study of the water, energy and biogeochemical cycles of the Amazon River basin (Junk, 1997; Melack et al., 2009). Indeed, covering about 20% of basin's surface area, with large temporal variability, the surface waters of the Amazon play a key role in the climate and in the maintenance of biodiversity. Amazon surface waters are a major source and sink of carbon dioxide (Abril et al., 2014; Amaral et al., 2020; Raymond et al., 2013) and the largest natural geographic source of methane in the tropics (Kirschke et al., 2013; Melack et al., 2004; Pangala et al., 2017; Pison et al., 2013). In this context, understanding the dynamics of surface water extent is of primary importance to Amazon hydrology, biogeochemistry processes and their link with climate, for effective management of water and fisheries resources (see Section 6.3) and for a disaster management for cities which are under flood risk (e.g., Iquitos, Porto Velho, Rio Branco, Cruzeiro do Sul). This is particularly true in the context of current global changes that impact the Amazon (see Section 6.4), with intense drought and flood events that recently affected large areas of this region (Davidson et al., 2012; Jiménez-Muñoz et al., 2013; Marengo et al., 2008, 2011). In addition, monitoring the variations of surface water hydrological conditions is key to support the development of models of the Amazon water cycle and its surface hydrology (see Section 6.2).

Characterizing the distribution and quantifying seasonal and interannual variations in the extent of surface waters at the scale of the Amazon basin is a challenge given their large variety and variability, and the presence of cloud cover and forest vegetation. Early estimates of the distribution of surface water for large areas were based on static databases from aeronautical charts and aerial photographs, which often reflected the maximum open water extent (Cogley, 2013; Matthews & Fung, 1987) and did not provide information on their temporal and spatial variations. The Global Lakes and Wetlands Database (Lehner & Döll, 2004) estimates the extent of floodplains and wetlands in the Amazon of ~300–350 × 10^3 km^2, but with large uncertainties (Davidson et al., 2018). The advent of satellite observations now allow monitoring the large-scale dynamic of surface waters, including those in the Amazon basin (Alsdorf et al., 2007; Prigent et al., 2007) enabling progress on understanding of the associated physical, biogeochemical, environmental and ecological processes.

Different RS-based techniques, using observations made in a wide range of the electromagnetic spectrum (visible, infrared, and microwave; Melack et al., 2004; Prigent et al., 2016), have been developed, with varying degrees of success, to derive quantitative estimates of the extent and dynamics of surface waters and aquatic systems in the Amazon (Table 4). They encompass a wide range of spatial and temporal resolutions, often based on a trade-off between temporal and spatial coverages. Observations with low spatial resolution (e.g., ~10–50 km from passive microwave sensors) are generally limited to the detection of relatively large inundated areas, or regions where the cumulative area of small areas represents a fairly large portion of the satellite footprint. They have the advantage of frequent temporal coverage, sometimes daily. High-resolution observations (e.g., <100 m from SAR for instance) provide information at a fine spatial scale but have low temporal frequency, often limiting observations over large areas to a few times per season. Optical and infrared observations offer good spatial and temporal resolution but have limited capabilities in the tropical Amazon region as they are unable to penetrate clouds and dense vegetation.

Passive microwave observations have demonstrated their usefulness for observing surface water and flood extent and provided some of the first estimates of Amazon surface water extent from satellite (Giddings & Choudhury, 1989) as reviewed in Kandus et al. (2018). Emissivities (and brightness temperatures) are sensitive to the presence of surface water (Choudhury, 1991; Sippel et al., 1994) with a decrease in emissivity in both linear polarizations (horizontal and vertical) and an increase for the difference in polarization, especially at low frequencies, due to the different dielectric properties between water, soil and vegetation. Surface water and inundation patterns in the large floodplains of the central Amazon (Sippel et al., 1998) and South America (Hamilton et al., 2002) were derived by analysis of the 37-GHz polarization difference observed by the Scanning Multichannel Microwave Radiometer (SMMR; Nimbus-7 satellite, 1979–1987). By developing a relationship between the total flooded area along the Amazon River main stem and the monthly means of river stage at Manaus, they provided the first 94-year reconstruction of flooded area from the river stage in situ record, estimating the long-term mean of the flooded area along the Amazon River

Table 4
RS-Based Approaches Developed to Monitor the Extent of Surface Water in the Amazon (Non-Exhaustive List)

RS approaches	References	Sensors/Satellites (Product name)	Original area of study	Spatial/temporal resolution	Time span
Passive Microwaves	Giddings and Choudhury (1989)	SMMR on Nimbus 7	4 major river basins of SA	~25 km/Monthly	1979–1985
	Sippel et al. (1994)	SMMR on Nimbus 7	Central Amazon and floodplains	~25 km/Monthly	1979–1985
	Sippel et al. (1998)	SMMR on Nimbus 7	Amazon River and tributaries	~25 km/Monthly	1979-1985 (and 1902–1995 reconstruction)
	Hamilton et al. (2002)	SMMR on Nimbus 7	6 major floodplains over SA.	~25 km/Monthly	1979–1987
	Brakenridge et al. (2007)	AMSR/E on Aqua	Global	~25 km/daily	2002–2011
	Parrens et al. (2017)	SMOS (SWAF)	Amazon basin	~25–50 km/3-day	2009–present
Active Microwaves	Hess et al. (2003)	SAR on JERS-1	Central Amazon	100 m/Sep–Oct 95 and May–Jun 96	Sept–Oct 95 and May–Jun 96
	Bourrel et al. (2009)	SAR on ERS-2/RADARSAT	Bolivian Amazon	2 RADARSAT (50 m)/3 ERS (15 m) images	1996–1998
	Arnesen et al. (2013)	ScanSAR mode on ALOS/PALSAR	Lower Amazon River floodplain	100 m/12 ScanSAR images	2007–2010
	Ferreira-Ferreira et al. (2015)	SAR on ALOS/PALSAR	Central Amazon floodplain	12.5 m/13 ScanSAR fine bream images	2007–2010
	(Hess et al., 2015)	SAR on JERS-1	Amazon basin	100 m/Sept–Oct 1995 and May–Jun 1996	Sept–Oct 1995 and May–Jun 1996
	Chapman et al. (2015)	ScanSAR mode on ALOS/PALSAR	Amazon basin	100 m/323 ScanSAR images	2007–2010
	Ovando et al. (2016, 2018)	ScanSAR mode on ALOS/PALSAR and MODIS reflectance	Bolivian Amazon wetlands	100 m/45 ScanSAR and 500 m/8-day MODIS images	2007–2009 and 2001–2014
	Park and Latrubesse (2017)	SAR on ALOS/PALSAR	Amazon floodplain (Miratuba)	12–350 m/19 images	2006–2008
	Pinel et al. (2019)	SAR on ALOS/PALSAR	Amazon/Solimoes River (Janauaca)	30 m/23 images	2007–2011
	Resende et al. (2019)	SAR on ALOS/PALSAR	Central Amazon	25 m/56 images	2006–2011
	Rosenqvist et al. (2020)	ScanSAR on ALOS-2 PALSAR-2	Amazon basin	50 m/Yearly minimum and maximum	2014–2017
Optical and infrared	Yamazaki et al. (2015)	Landsat (G3WBM)	Global	90 m/4 scenes of surface body freq. at 5-year interval	1990–2010
	Pekel et al. (2016)	Landsat (GSW)	Global	30 m/Surface water occurence	1984–2015
	Allen and Pavelsky (2018)	Landsat (GRWL)	Global	30 m/static widths and areas	–
	Souza et al. (2019)	Landsat	Amazon basin	30 m/Surface water changes	1985–2017
Multi-satellite techniques (passive microwaves in combination with other RS observations)	Prigent et al. (2007, 2020)	SSMI/AVHRR/ERS (GIEMS)	Global	~25 km/monthly	1992–2015

Table 4
Continued

RS approaches	References	Sensors/Satellites (Product name)	Original area of study	Spatial/temporal resolution	Time span
	Schroeder et al. (2015)	SSM/I, SSMIS, ERS, QuikSCAT, ASCAT (SWAMPS)	Gobal	~25 km/monthly/daily	1992-present
	Aires et al. (2013)	GIEMS/JERS-1 SAR	Central Amazon	500 m/monthly	1993–2007
	Fluet-Chouinard et al. (2015)	GIEMS downscalled (named GIEMS-D15)	Global	500 m/max./min./average	1993–2007
	Aires et al. (2017)	GIEMS downscalled (named GIEMS-D15)	Global	90 m/monthly	1993–2007
	Parrens et al. (2019)	SMOS downscalled (named SWAF-HR)	Amazon basin	1 km/3-day	2010–2016

Note. References, sensor/satellite name, product name (when available), original area of study, spatial/temporal resolution and time span of data availability are shown.

main stem to be ~47,000 km^2. Those studies have been followed by passive microwave-derived products of surface water extent over the Amazon, using Special Sensor Microwave/Imager (SSM/I), Advanced Microwave Scanning Radiometer (AMSR-E; Brakenridge et al., 2007) and most recently Soil Moisture Ocean Salinity (SMOS) observations (Parrens et al., 2017). Parrens et al. (2017) used the microwave L-band (1.4 GHz) observations from 2010 to 2017 to map the temporal evolution of the Amazon water bodies at coarse spatial resolution (~50 km) and weekly temporal resolution (product named SWAF) with the ability, thanks to the L-Band frequency, to better retrieve water under dense canopy. Passive microwave observations have inherent limitations because of their ground footprints in the typical order of 25–50 km, and their relatively low spatial resolution is often insufficient to observe small water bodies.

Multi-satellite methodologies that combine the complementary strengths of different types of satellite observations to retrieve surface water extent and their dynamics expand the information provided by passive microwave radiometers (Table 4). Though designed originally for global scale applications, these approaches have been evaluated in the Amazon basin. The Global Inundation Extent from Multi-Satellite (GIEMS, Papa et al., 2010; Prigent et al., 2007, 2016, 2020) or the Surface WAter Microwave Product Series (SWAMPS) Inundated Area Fraction (Schroeder et al., 2015) detect and quantify multi-decadal variability of surface water extent over tropical environments (Frappart et al., 2008; Papa et al., 2008, 2013). The current version of GIEMS is available at ~25 km spatial resolution on a monthly basis from 1992 to 2015 (GIEMS-2, Prigent et al., 2020, Figure 6a), while SWAMPS offers current and near-real-time information (Jensen et al., 2018). The use of these passive microwave-derived data sets helped reveal the sources and characteristics of the flood pulse and annual flood wave along the Amazon River and major tributaries. They contributed to show at basin scale the water extent seasonality, with a high flood season in May-June and low flood season in November in the central Amazon floodplain. At basin-scale, Amazon surface water extent (Figure 6b) varies from ~100,000 km^2 (low season) to almost ~400,000 km^2 (high season), but with large interannual variability, mainly driven by droughts (1998, 2005, and 2010) or floods (1997, 2014) extreme events (Papa et al., 2010; Prigent et al., 2020). However, the maximum surface water extent from GIEMS and SWAMPS are lower than those from SAR estimates (Figure 6b).

Prigent et al. (2007) showed that seasonal flooding differed between the north and south parts of the basin due to seasonal differences in precipitation. Papa et al. (2008) reported a phase lag in precipitation, flood extent, and peak flows at the basin scale, suggesting as in Richey et al. (1989), that floodplains in large basins such as the Amazon can store a large volume of water and alter the water transport. Richey et al. (1989) applied a simple water routing scheme and estimated that up to 30% of the discharge of the Amazon River is routed through the floodplains. However, studies such as Getirana et al. (2012), based on the large-scale hydrological model that used GIEMS to evaluate their floodplains simulations, suggested instead that the

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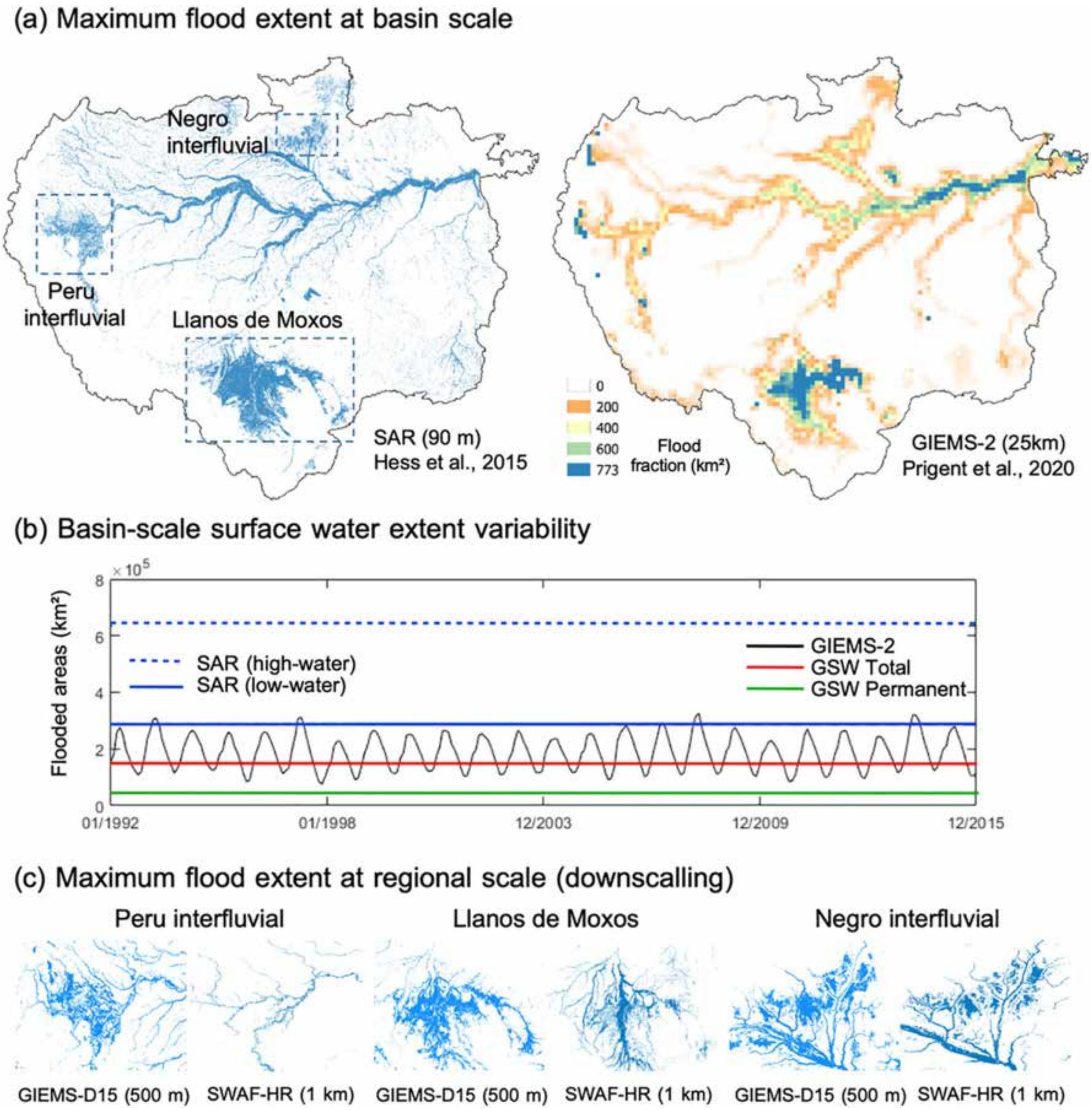

Figure 6. Surface water extent of the Amazon basin. (a) Map of maximum wetland and surface water extent (high water season) from JERS-1 SAR (Hess et al., 2015) and map of annual maximum surface water extent (fraction in km^2 for each 773 km^2 pixel) averaged over 1992–2015 from GIEMS2 (Prigent et al., 2020). (b) Basin-scale monthly mean surface water extent variability for 1992–2015 from GIEMS2 (solid black line) along with estimates of JERS-1 SAR-derived wetland and flooded area for high-water (dashed blue line) and low-water (solid blue line) seasons. Also shown are the Global Surface Water (GSW, Pekel et al., 2016) permanent surface water extent (green line, GSW permanent) and the total (permanent plus transitory) surface water extent at maximum (red line, GSW Total). (c) Map of maximum surface water extent at regional scale (boxes in panel (a) indicate the locations) from GIEMS-D15 (Fluet-Chouinard et al., 2015) and SWAF-HR (Parrens et al., 2019).

actual value might be more than 5%. Furthermore, Sorribas et al. (2020) reported that the ratio between river-floodplain discharge and basin discharge ranged between 5% and 40%, which is comparable to the range estimated from observations by Richey et al. (1989) and Alsdorf et al. (2010) who used gravimetric and imaging satellite methods to estimate the amounts of water seasonally filling and draining from the mainstem Amazon floodplain. Hence, there is a need to better understand the processes that control Amazon inundations in order to quantify the various fluxes across floodplain environments, as is evident in applications of regional-scale flooding models (Rudorff et al., 2014b).

Synthetic aperture radars are active radar instruments that measure the backscatter of the observed surface at an angle of incidence (off-nadir), regardless of cloud cover, and allow delineation of open surface waters and inundated area with vegetation with a typical spatial resolution of 10–100 m (Behnamian et al., 2017; Hess et al., 1990; Kasischke et al., 1997) The Spaceborne Imaging Radar-C (SIR-C) experiment provided high quality, multi-band and multi-polarization data for the Amazon that led to the development of new approaches using SAR. Alsdorf et al. (2000) demonstrated the ability of interferometric analyses to detect centimeter-scale variations in slope across the Amazon rivers and floodplains (see Section 4.1). Hess et al. (1995) developed algorithms to detect inundation and vegetation within Amazon wetlands that benefitted from modeling of interactions between vegetation and radar, including the double-bounce effect, also done as part of SIR-C (Wang et al., 1995). Understanding derived from this led to the use of data provided by the Japan Earth Resources Satellite-1 (JERS-1) to produce the first high-resolution wetland map for the central Amazon region under low-water and high-water conditions at 100-m resolution (Hess et al., 2003). These results were validated with airborne, high-resolution, videography transects throughout the imaged area (Hess et al., 2003). Hess et al., (2003) found that 17% of the 1.77 million km^2 study area is occupied by wetlands, of which 96% are inundated at high water and 26% at low water. Flooded forests accounted for nearly 70% of the overall wetland area, but proportions of the wetland habitats showed large regional variations related to floodplain geomorphology. Those new estimates of the large inundated area were of major importance to understand the outgassing of methane and carbon dioxide from Amazon flooded areas (see Section 6.3).

The JERS-1 SAR estimates were extended to the entire wetlands of the lowland Amazon basin (region <500 m asl) (Figure 6a; Hess et al., 2015), currently one of the standards for comparison with other satellite-derived products. It estimates the flooded extent (Figure 6b) to be $\sim 2.85 \times 10^5$ km^2 for the low water season (October–November 1995) and of $\sim 6.34 \times 10^5$ km^2 for the high water season (May–July 1996). An interesting comparison is one made for the central corridor of the Amazon (Prigent et al., 2007) between GIEMS and the 100 m resolution L-band JERS-1 SAR mosaic of Hess et al. (2003) for low water (September-October 1995) and high water (May-June 1996). For both seasons, the spatial structures are similar but estimates of the surface water extent observed by SAR (118,000 km^2 for the low water season, 243,000 km^2 for the high water season) are larger than the area estimated by GIEMS (105,000 km^2 for the low water season, 171,000 km^2 for the high water season). Thanks to its better spatial resolution, the SAR estimates are capable to discriminate smaller water bodies than GIEMS (typically water bodies smaller than 80 km^2 that is, 10% of a GIEMS pixel), especially for the low water season. For the entire Amazon basin, the basin-wide estimates from GIEMS do not match the basin-wide SAR (Figures 6a and 6b) as reported in Hess et al. (2015) which suggested that global data sets derived from lower-resolution sensors or optical sensors capture less than 25% of the wetland area mapped by the SAR.

The use of multi-temporal SAR coverage, such as the ScanSAR mode of ALOS/PALSAR, provide variations of flood extent at the scale of floodplain units, for example, Curuai floodplain along the lower Amazon River (Arnesen et al., 2013), Mamiraua floodplain (Ferreira-Ferreira et al., 2015) or inundation patterns in central Amazon (Pinel et al., 2019; Resende et al., 2019). Rosenqvist et al. (2020) generated annual maximum and minimum inundation extent maps over the Amazon using ALOS-2/PALSAR-2 ScanSAR, in line with previous inundation maps by L-band JERS-1 and ALOS/PALSAR radar classifications of the inundation (Chapman et al., 2015). At the regional scale, Bourrel et al. (2009) mapped the floods in the Bolivian Amazon from SAR C-Band microwave data of RADARSAT and ERS-2. Over the same region, the surface water dynamics of the Bolivian Amazon wetlands (Ovando et al., 2018), as well as the characterization of extreme flood events (Ovando et al., 2016) were investigated by combining ALOS/PALSAR SAR observations with MODIS multi-temporal flood maps and altimetry-derived water level variations (ENVISAT & SARAL). Other SAR satellite missions, such as the Copernicus Sentinel-1 SAR (launched in 2014), which offer a global revisit of 6–12 days, have not been yet fully exploited in the Amazon but offers new opportunities for mapping the spatial and temporal variations of surface waters at a fine scale in tropical environments. The near-future launch of SAR satellites, such as NISAR and SWOT (Prigent et al., 2016), will offer new opportunities to monitor Amazon surface water with dedicated sensors.

Optical and infrared imagery observations (e.g., Landsat, SPOT, QuickBird, Ikonos, AVHRR, MODIS, and Sentinel 2A/B) offer high spatial and temporal resolutions (~1–500 m, sub-daily to weekly) but in tropical environments, they are generally limited by the inability to penetrate clouds and dense vegetation. Therefore, assembling cloud-free coverage during the rising flood season of the central Amazon remains challenging (Asner, 2001; Hess et al., 2015; Klein et al., 2015). Nevertheless, classification of optical imagery using water indexes and related methods, as reviewed by Huang et al. (2018), enables to estimate flood frequency based on temporal maps of surface water cover, and despite the limitations from vegetation canopy and cloud cover, this type of data can be of value to monitor open surface water. Several studies (Table 4) based on Landsat observations created global databases of the area of rivers (Global River Widths from Landsat -GRWL; Allen & Pavelsky, 2018) and surface water (Pekel et al., 2016; Yamazaki et al., 2015) which can be used at the basin scale. Based on the decadal-scale monitoring of Landsat missions, the Global Surface Water data set (GSW, Pekel et al., 2016) uses 3 million images over 32 years (from 1984 to 2015) at a 30 m spatial resolution to derive a monthly record of water presence in classifying each Landsat pixel as open water, land, or non-valid observation using an expert system. In the Amazon basin, GSW estimates of surface water extent (permanent and total as the sum of permanent and transitory water bodies) are lower than the estimates from other RS-based techniques such as SAR or GIEMS (Figure 6b) and comparison of GSW with GIEMS-D3 (see further below) found seasonal water bodies in savannas and forest floodplains were not detected properly (Aires et al., 2018). Souza et al. (2019) developed another Landsat classification to estimate long-term changes in Amazon surface waters revealing the recent increase in areas associated with hydropower lakes. Recent satellite missions such as Sentinel 2A/B (since 2015, with 10 m spatial resolution at 5–10-day intervals, Pham-Duc et al., 2020) or programs such as the RapidEye (since 2008, 5 m spatial resolution and a temporal resolution of 1–5.5 days, Garousi-Nejad et al., 2019) or the PlanetScope (CubeSats, since 2014, with 3–5 m spatial resolution and daily revisit time; Cooley et al., 2019) constellations might bring new opportunities to study fine scale surface water extent of the Amazon.

In order to take advantage of the complementary strengths of various observations, for instance, the low resolution but long-term estimates of passive microwave versus the high resolution but limited in time observations from SAR, a downscaling methodology combining both estimates have been developed to retrieve monthly central Amazon at ~500 m spatial for the 1993–2007 period (Aires et al., 2013). Several other studies based on downscaling approaches using a floodability index provide high resolution maps of surface water extent over the Amazon, such as GIEMS-D15 (Fluet-Chouinard et al., 2015; ~500 m spatial resolution and its 1-km adaptation as in Reis et al., 2019) and GIEMS-D3 (Aires et al., 2017, 90 m). Similarly, Parrens et al. (2019) proposed a downscaling methodology based on multi-source RS data (SMOS SWAF; combined with a global DEM and GSW data set) to map Amazon inland water under vegetation at ~1 km spatial resolution every 3 days for 2010–2016 (named SWAF-HR). Figure 6c shows maps of maximum surface water extent from GIEMS-D15 and SWAF-HR for three regions, including interfluvial wetlands. Such observations are valuable to wetland conservation decisions, as the timing and duration of inundation often determine ecological characteristics and the provision of ecosystem services. For instance, Reis et al. (2019) classified Amazon wetlands according to the timing and duration (months per year) of inundation detected with GIEMS-D15, and their link to precipitation regimes. It revealed that permanently inundated wetlands account for the largest area and are mainly floodplains located in the lowlands of the catchment. Seasonally inundated wetlands varied in the duration of inundation reflecting different rainfall and hydrological regimes. These regional differences in inundation characteristics are important to conservation planning and wetland management especially in the context of anthropogenic interventions such as dams and waterway construction.

Finally, new RS techniques and methodologies are continuing to be developed and can help monitor the surface water extent of the Amazon basin. The potential for Global Navigation Satellite System-Reflectometry (GNSS-R) has been explored (Chew & Small, 2020; Jensen et al., 2018; Rodriguez-Alvarez et al., 2019) using Cyclone GNSS (CYGNSS) constellation of GNSS-R satellites and a simple forward model that demonstrates how surface reflectivity measured by CYGNSS can capture flooding dynamic over the region.

In Section 5.1 "Methods for Measuring Area" of Alsdorf et al. (2007), the authors suggested that "*Perhaps the best opportunity in the next few years for routine measurements of inundated area will result from the Japan Aerospace Exploration Agency's ALOS mission*". More than a decade later, it is worth noting that the extent and variability of surface water of the Amazon are still one of the most studied variables of the hydrological cycle, but that studies using ALOS observations remain recent and limited. Further studies and new observations are required to fully characterize Amazon surface water extent and the processes that drive the patterns and dynamics. In particular, polarimetric and interferometric L-band SAR data from the forthcoming NASA/ISRO SAR mission and the Ka-band Radar Interferometer (KaRIn) swath observations from the forthcoming SWOT mission will be capable of enhanced monitoring and comprehensive survey of large-scale surface water extent and dynamics of the Amazon.

4.3. Floodplain and River Channels Topography

Along the Amazon River, the floodplain has many lakes and channels that vary in extent, depth, and connectivity (Hess et al., 2015; Rudorff et al., 2014b; Trigg et al., 2012). This complex topography affects the water flow through river-floodplain water exchanges, which in turn, are important for carbon, nutrients, and sediment fluxes (Melack et al., 2009; Walcker et al., 2021). Accurate topographic information is essential for the characterization of the surface water in the floodplain, particularly for hydraulic numerical modeling (Baugh et al., 2013; Paiva, Buarque, et al., 2013; Rudorff et al., 2014a). Furthermore, topographic mapping is required for understanding the morphology and morphodynamics of the river channels and lakes. The SRTM DEM is a global topographic data set with 30–90 m of spatial resolution and accuracy of 8 m (Rodríguez et al., 2006) generated from C-band interferometry (Farr et al., 2007) and has been widely used in hydraulic simulations and geomorphic characterization of the Amazon floodplains (Figure 7a). However, the data are affected by vegetation cover and have errors such as absolute bias, speckle noise (granular aspect in the image due to the random presence of pixels with extreme values), and stripe noise (Rodríguez et al., 2006). It is also not capable of describing bathymetry of inland water bodies as it observed surface water elevation only once.

The application of topographic data, such as SRTM DEM, together with radar (e.g., RADAM, JERS-1) and optical (e.g., Landsat) images allowed the geomorphological characterization of floodplains and river channels of the Amazon basin. Sippel et al. (1992) described lakes of different shapes based on RADAM maps along different sections of the main stem Solimoes/Amazonas rivers and their major tributaries. Latrubesse and Franzinelli (2002) and Mertes et al. (1996), described geomorphologically distinct regions along the upper and middle reach of the Amazon River. Scroll-bar topography, which forms long and narrow lakes, and oxbow lakes, located in abandoned river meanders, are dominant in the upstream reaches (Mertes et al., 1996; Figure 7). Downstream reaches are characterized by large, shallow lakes formed by the overbank deposition of fine sediments in a very flat floodplain topography (Latrubesse & Franzinelli, 2002; Mertes et al., 1996; Figure 7). Active deposition of sediments across the floodplains was also identified and described by Lewin et al. (2017), Park and Latrubesse (2019), and Rudorff et al. (2018) using RS data. Ahmed et al. (2019), Constantine et al. (2014), Peixoto et al. (2009), Rozo et al. (2012), and Sylvester et al. (2019) characterized the channel's migration of rivers and floodplains. Sediment supplies play an important role in the evolution of Amazonian rivers, as the rivers with high sediment loads experience faster meander migration and higher cutoff rates than rivers with lower sediment loads (Constantine et al., 2014). Large and rapid geomorphological changes can also arise due to anthropogenic pressures such as livestock and channel irrigation. These may be the causes of the progressive erosion of a channel along the lower Amazon River that captured almost all discharge from the lower Araguari River, which previously had flowed directly to the Atlantic Ocean (dos Santos et al., 2018; described in more details in Section 6.4).

In order to improve the applicability of SRTM data to hydraulic modeling of the Amazon, various techniques were developed such as the removal of the vegetation height (Baugh et al., 2013; O'Loughlin et al., 2016; Paiva, Buarque, et al., 2013; Paiva, Collischonn, & Tucci, 2011; Pinel et al., 2015; Rudorff et al., 2014a; Yamazaki et al., 2017), the interferometric bias (Pinel et al., 2015; Rudorff et al., 2014a), as well as smoothing and pit removal (Yamazaki, Baugh, et al., 2012). Despite the better topographic representation achieved by these methods, topographic information below the water surface cannot be recovered from SRTM. Also, the SRTM data set relies on one only overpass in February 2000. Therefore, some processes, such as infilling and drainage of the floodplain, may not be well represented in the numerical models. River bathymetry is also key information that is not systematically resolved. Recently Brêda et al. (2019) demonstrated the potential of assimilating satellite altimetry data into hydraulic models for its estimation. To estimate the topography in seasonally flooded areas, Bonnet et al. (2008) combined SWE with flood extents derived from JERS-1 images to estimate a bathymetric DEM of the Curuai floodplain. Park et al. (2020) related water depth and a flood frequency map, derived from surface water mapping, to infer the Curuai bathymetry. Fassoni-Andrade, Paiva, Rudorff, et al. (2020) developed and applied a systematic method to estimate floodplain topog-

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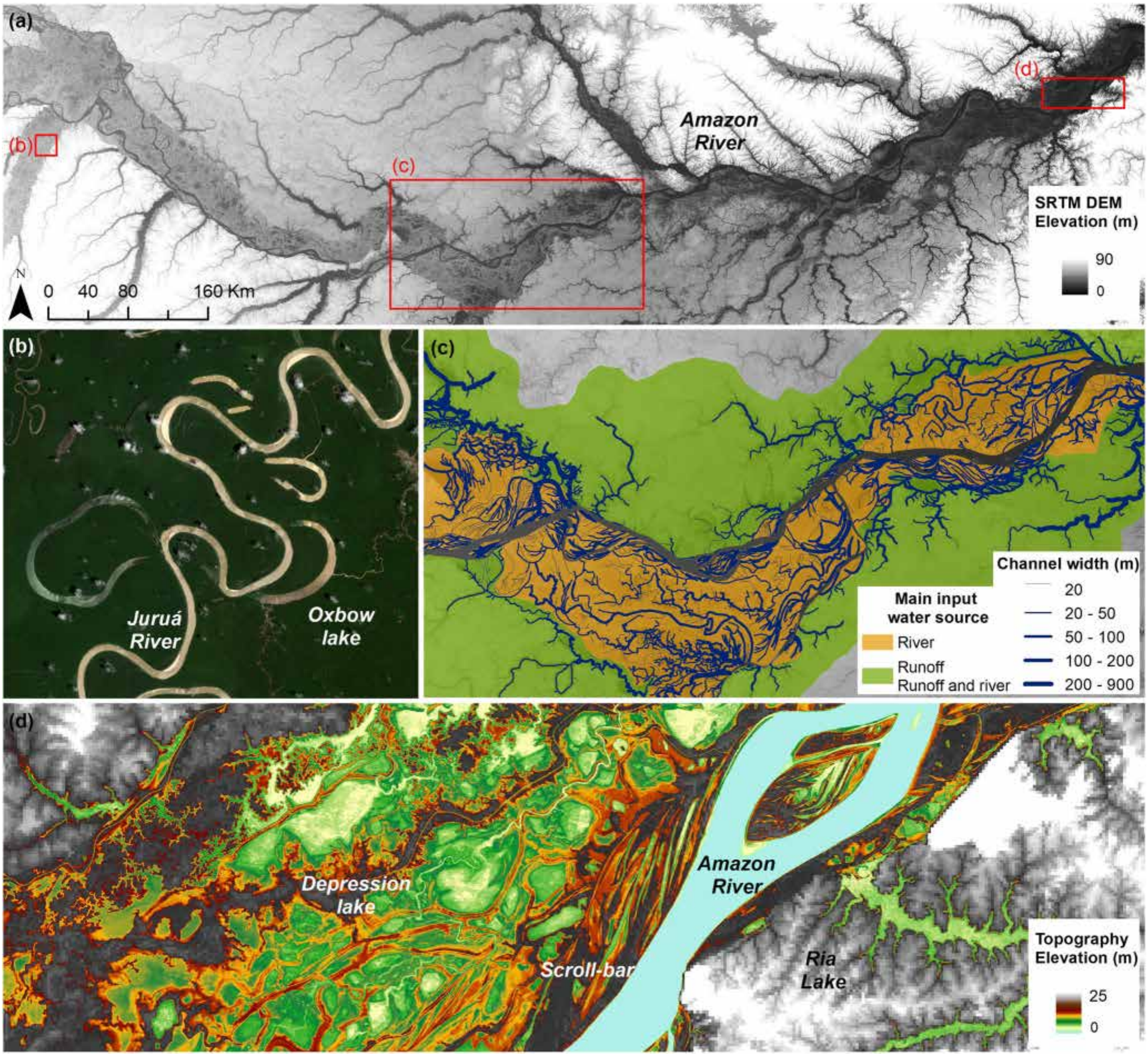

Figure 7. (a) Shuttle radar topography mission digital elevation model in central Amazon. (b) Oxbow lakes in Juruá River (Sentinel-2, October of 2020). (c) Channel width in the floodplain (adapted from Trigg et al., 2012). (d) Topography elevation of the floodplain channels and lakes (adapted from Fassoni-Andrade, Paiva, Rudorff, et al., 2020).

raphy using a combination of flood frequency maps derived from optical RS and ancillary in situ water level data archives (Figure 7d). This was the first systematic and extensive mapping of a seasonally flooded area in a wetland, showing floodplain depths less than 5 m (15 m) in low (high) water, and that active storage volume in the open-water floodplain varies 104.3 km^3 on average each year. This data set was complemented over permanently flooded regions by a compilation of digitized nautical charts from the Brazilian Navy. Recently, Fassoni-Andrade et al. (2021) applied this methodology to the Amazon estuary showing the morphology of the intertidal floodplain.

The bathymetric information in permanently flooded areas relies on in situ field surveys. Among the studies cited here, only a few obtained in situ bathymetric information in floodplains (Bonnet et al., 2008; Fricke et al., 2019; Pinel et al., 2015) and rivers (Wilson et al., 2007). Additional studies with detailed bathymetry include Lesack and Melack (1995), Barbosa et al. (2006), Panosso et al. (1995), and Trigg et al. (2012). As part of the first hydrological budget of an Amazon floodplain lake, Lesack and Melack (1995) surveyed the lake's bathymetry, which was subsequently used in the hydrological model of Ji et al. (2019). Panosso et al. (1995) conducted a bathymetric survey of Lake Batata, located near the confluence of the Trombetas River and the Amazon River. This lake received tailings from bauxite processing and the estimate was used for conservation and recovery studies. Barbosa et al. (2006) conducted an extensive bathymetric survey of the Lake Grande do Curuai floodplain, in the eastern Amazon basin. The bathymetry was used to estimate volume, in hydraulic simulation (Rudorff et al., 2014a) and topographic assessment (Fassoni-Andrade, Paiva, & Fleischmann, 2020). Trigg et al. (2012) illustrated the first systematic characterization of floodplain channels in central Amazon based on Landsat imagery and field survey (Figure 7c). Floodplain channel widths vary considerably (10–1,000 m), and channel depths are related to the local amplitude of the Amazon River flood wave (∼10 m), and deeper when subject to local runoff.

Many advances have been made to characterize the topography of rivers and floodplains using RS techniques, among the promising prospects for new DEMs (e.g., The L-band reduces the systematic positive bias of vegetation due to its ability of penetrating the canopy. Images from the NISAR mission, a bi-band SAR satellite to be launched in 2022 with global coverage and revisiting periods of 12 days will improve the availability of L-band radar data. The SWOT mission will simultaneously measure the SWE and water extent, opening up new opportunities to create and improve new techniques to estimate river and floodplain topography. New unexplored data from ICESat-2 satellite (launched in 2018) could be useful for topography estimation and validation.

4.4. Water Quality: Sediments, Chlorophyll, and Colored Dissolved Organic Matter

According to their physical and chemical water characteristics, rivers of the Amazon basin are classified into three types: white, black, and clear-waters rivers (Junk et al., 2011; Sioli, 1956). Nutrient-rich whitewater rivers, such as Madeira and Solimões rivers, which account for 98% of Amazon River's sediment discharge to the Atlantic Ocean are dominated by inorganic sediments mainly originated from the Andes (Almeida et al., 2015; Meade, 1994). Blackwater rivers (e.g., Negro River; Figure 8a) are rich in dissolved organic matter derived from podzolic soils (Bouchez et al., 2011; Marinho et al., 2020). Clear-water rivers (e.g., Tapajós River; Figure 8b) are characterized by nutrient-poor, low sediment, and dissolved organic matter concentration (Junk et al., 2015). The water-type diversity and the pathways throughout the Amazon floodplain have significant implications for floodplain lakes and contribute to their high biodiversity (Junk et al., 2011; Thom et al., 2020).

A feasible way to monitor the aquatic system's biogeochemical properties and water paths between the rivers and floodplain lakes is through satellite RS. The interaction between electromagnetic radiation and water bodies, described by radiative transfer theory (Mobley, 1994), allows the development and calibration of algorithms for estimating optically active constituents (OACs: Total Suspended Sediments -TSS; Phytoplankton pigments such as Chlorophyll-a (Chl-*a*) and Phycocyanin; and Colored Dissolved Organic Matter [CDOM]) in the water bodies. These OACs influence the underwater light field and, therefore, the inherent (e.g., absorption and backscattering coefficient) and apparent optical properties (e.g., Remote Sensing Reflectance–R_{rs}) of the water bodies.

There are significant challenges applying RS to the monitoring of Amazon basin aquatic ecosystems: (a) frequent cloud cover makes it difficult to acquire images, (b)) the optical complexity of the waters that flow throughout the basin, characterized by high variability in the concentration of the OACs, (c) the lack of sensors with high radiometric, spectral, spatial resolution, and signal-to-noise ratio to detect the small changes in upwelling radiance from the water column, and (d) the difficulty of using RS in narrow rivers and small lakes. These challenges have existed since the beginning of RS applications to study Amazonian aquatic ecosystems in the early 1980s when the studies were focused on calibration/validation of algorithms based on in situ data. These methods were based mostly on empirical approaches (Bayley & Moreira, 1978; Bradley, 1980; Mertes et al., 1993), with acceptable accuracy limited in time and space to the data set for which the algorithm was developed (Matthews, 2011; Odermatt et al., 2012). In the last decade, efforts have been made to adapt ocean color protocols (Mueller et al., 2003) to acquire inherent optical properties (IOPs) of the Amazonian waters (de Carvalho et al., 2015; Costa et al., 2013; Jorge et al., 2017; Maciel, Barbosa, et al., 2020; Pinet et al., 2017; Valerio et al., 2018), allowing for the development of semi-analytical algorithms (SAA). As

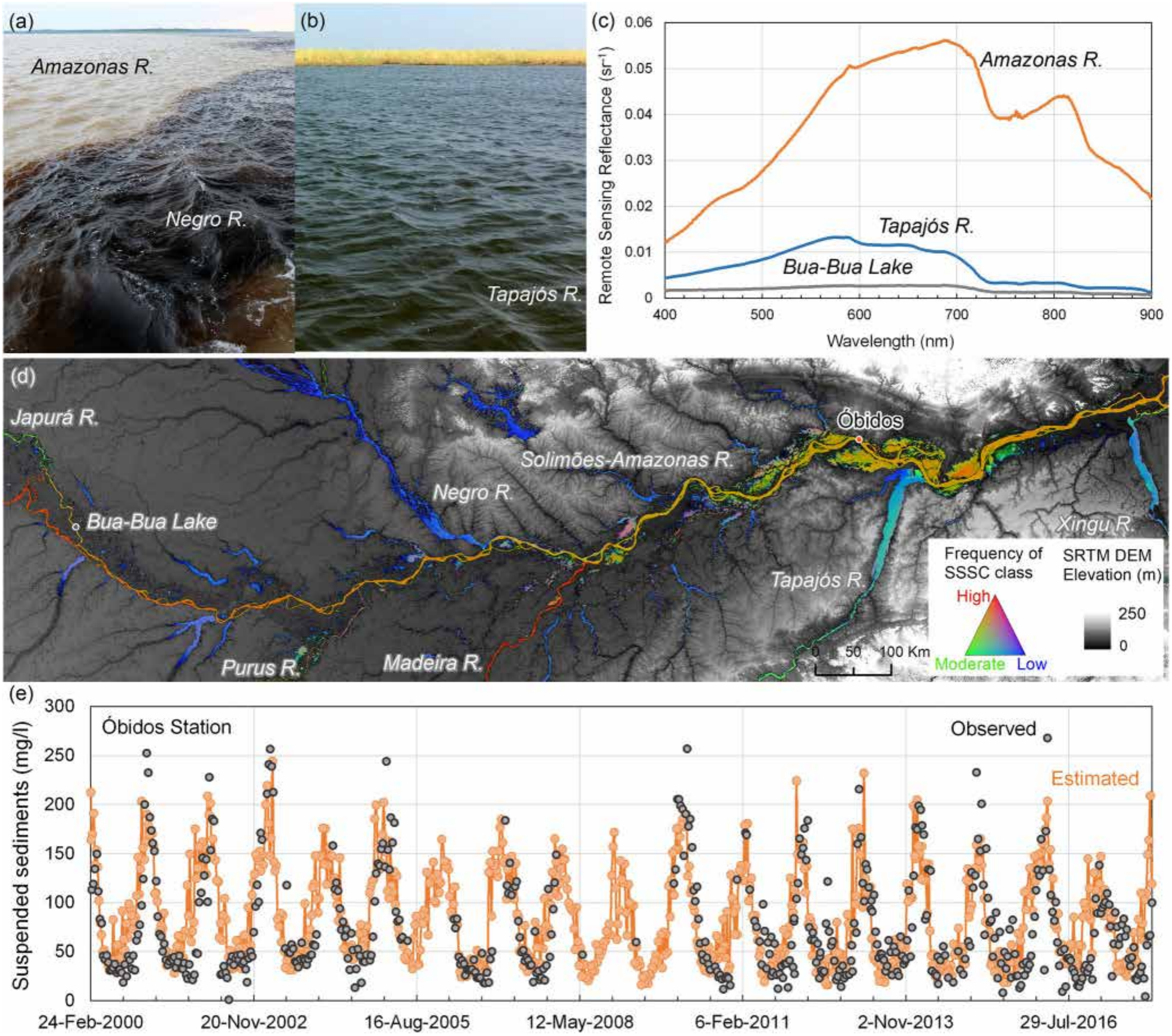

Figure 8. (a) Examples of white and black, and (b) Clear waters. (c) Examples of spectra of three water types (Source: Labisa; http://www.dpi.inpe.br/labisa/): white water - Amazon River (TSS of 288.5 mg L^{-1}; Chl-*a* of 2.0 μg L^{-1}; aCDOM in 440 nm of 1.3 m^{-1}); clear water—Tapajós River (TSS 5.7 mg L^{-1}; Chl-*a* of 10.8 μg L^{-1}; aCDOM in 440 nm of 1.2 m^{-1}); black water - Bua-Bua Lake (TSS 7.4 mg L^{-1}; Chl-*a* of 3.6 μg L^{-1}; aCDOM in 440 nm of 2.9 m^{-1}). (d) Spatial variability of suspended sediments in the central Amazon (adapted from Fassoni-Andrade & Paiva, 2019). (e) Suspended sediment time-series in situ (observed) and satellite-based Moderate Resolution Imaging Spectroradiometer (estimated) obtained from the HYBAM monitoring system (http://hidrosat.ana.gov.br).

the apparent optical properties (AOPs) are proportional to the IOPs, SAA uses an inversion process based on radiative transfer theory to obtain IOPs from the AOPs. Once the IOPs are known, they are used to retrieve the OAC concentrations. Therefore, SAA algorithms better identify each constituent contribution, providing more comprehensive temporal and spatial coverage (Dekker, 1993; Novoa et al., 2017).

The flourishing of satellite RS in the second decade of the 21st century is due to two crucial technological advances. First, a new generation of sensors was better designed to study complex aquatic environments, with improved spectral and radiometric resolution (Landsat-8, Sentinel-2, and CBERS-04A). Second, the unprecedented increase in computing performance and data storage has improved image processing capability. However, the low radiometric resolution provided by sensors onboard earlier Landsat (Landsat-5 and Landsat-7) satellites has not prevented the development of studies taking advantage of the substantial temporal database available (1972 to now) as reported in Lobo et al. (2015) and Montanher et al. (2018).

In preparation for new sensors, spectral behavior studies of Amazon water types among a wide range of OAC concentrations have been done (Barbosa, 2005; Nobrega, 2002; Rudorff, 2006). Those spectra were organized into a spectral library linked to OACs data to create reference spectra for water types classification (Lobo et al., 2012). The spectral library was used as input to a Spectral Angle Mapper algorithm for deriving water type maps from Hyperion and Medium Resolution Imaging Spectrometer (MERIS) images acquired simultaneously with field campaigns, with reasonable accuracies (48% and 67% for Hyperion and MERIS respectively). This updated library was applied to classify Brazilian water types (da Silva et al., 2020). In proof of concept studies, MODIS images from AQUA and TERRA satellites were successfully used for estimating Chl-*a* (Novo et al., 2006) and TSS (Espinoza-Villar et al., 2018; Fassoni-Andrade & Paiva, 2019; Marinho et al., 2018; Martinez et al., 2009) in Amazonian water bodies with a size compatible with the spatial resolution of the sensors.

Chl-*a* estimation, a proxy for phytoplankton abundance, remains challenging in the Amazon floodplain lakes due to high TSS masking chl-*a* spectral features (Lee et al., 2016) at some times (Barbosa et al., 2009, 2015; Bourgoin et al., 2007; Ferreira et al., 2013; Maciel et al., 2019). A spectral mixture algorithm was applied to overcome this problem in Curuai lake floodplain (Novo et al., 2006; Rudorff et al., 2006), and higher chlorophyll concentrations were observed in low water periods (November and December), as a result of lakes enriched by dissolved nutrients in less turbid waters (Novo et al., 2006). However, the empirical nature of those algorithms prevents their wide application. Therefore, new approaches have been investigated, including the use of semi-analytical algorithms (Flores Júnior, 2019). CDOM retrieval based on satellite imagery is scarce in Amazon lakes since the isolation of CDOM signature from the water leaving signal is complex in turbid waters (Jorge et al., 2021; Kutser et al., 2016). M. P. da Silva et al. (2019) proposed an empirical algorithm for estimating CDOM absorption at 440 nm from Sentinel-2/MSI images. Table 5 presents a summary of these studies.

There are many studies on sediment retrieval from satellite data. These studies are mainly focused on TSS estimates for rivers (Bernini et al., 2019; Espinoza-Villar et al., 2018; Kilham & Roberts, 2011; Lobo et al., 2015; Maciel, Novo, et al., 2020; Maciel et al., 2019; Montanher et al., 2014; Park & Latrubesse, 2014; Villar et al., 2013; Yepez et al., 2018) rather than for Amazon floodplain lakes (Alcântara et al., 2009; Fassoni-Andrade & Paiva, 2019; Maciel et al., 2019; Rudorff et al., 2006, 2007). However, most of them are based on empirical algorithms, and only recently, some semi-analytical algorithms became available (Table 5). The HYBAM observatory provides an example of systematically derived TSS concentration using empirical algorithms from MODIS at 16 stations (TSS time-series; http://hidrosat.ana.gov.br) in the main sediment-contributing rivers, including Amazon-Andean rivers in Peru and Bolivia (Espinoza Villar et al., 2012, 2018; Martinez et al., 2009; Villar et al., 2013). Figure 8e is an example of a suspended sediment time-series obtained from the HYBAM monitoring system in Amazon River between 1999 and 2017 and illustrates substantial variability of TSS concentration, ranging from 25 up to 250 mg L^{-1}.

Montanher et al. (2014) mapped TSS in five Amazonian rivers using multiple regression and observed that regional-calibrated algorithms performed better than global algorithms due to changes in the optical properties of rivers. Park and Latrubesse (2014) also observed that calibrating a separate empirical algorithm for low and high-water seasons provided better results for the Amazonian river waters. Marinho et al. (2021) calibrated an empirical algorithm using Sentinel −2/MSI red reflectance for retrieving sediment concentration in the Negro River (<10 mg·L^{-1}), characterized by high colored dissolved organic matter absorption (aCDOM >7 m^{-1} at 440 nm) and very low R_{rs} signals. Marinho et al. (2020) also showed that the backwater effect of the Solimoes River on the Negro River is the main factor contributing to the retention of 55% of the sediment load in the Anavilhanas Archipelago due to the low water slope and reduced flow velocity.

High variability in the OACs in floodplain lakes makes algorithm parametrizations difficult. For example, in the Curuai floodplain (lower reach of the Amazon River), TSS concentrations can vary from ∼5 mg L^{-1} in the high-water season up to 1,000 mg L^{-1} in the low water season due to sediment resuspension by winds (Bourgoin et al., 2007). Despite those issues, recent work provides successful TSS estimates in the floodplains of the lower Amazon River (Maciel, Novo, et al., 2020; Maciel et al., 2019).

Table 5
OACs Algorithms for the Amazon Basin

Study area	Sensor name	OAC	OAC range	At	Algorithm equation	Validation statistical results	Reference
Low Amazon	MODIS Terra	Chl-*a*	10-120 μgL^{-1}	E	$\text{Chl} = 3.9 * e^{0.0175*\text{fphy}}$	$R^2 = 0.76$, SE = 19 μgL^{-1}	Novo et al. (2006)
Mamirauá Sustainable Development Reserve	Sentinel-2	CDOM	~1–6 m^{-1}	E	$a_{\text{cdom}}(440) = 4.39^{B2/B3} + 0.59^{B6/B5} - 6.67$	$R^2 = 0.75$, MSE = 0.53 m^{-1}, %NMSE = 15.12%	M. P. da Silva et al., (2019)
Curuai Lake	Sentinel-2 and Landsat-8	TSS and TSI	7–43.5 mgL^{-1} (TSS)3.4–33.8 mgL^{-1} (TSI)	E	$\ln(TSS_{OLI}) = 9.656 + 1.672 * \ln(R_{rs}(550))$	$R^2 = 0.71$, MAPE = 16.81%, RMSE = 3.54	Maciel et al. (2019)
					$\ln(\text{TSI}_{\text{OLI}}) = 10.73 + 2.08 * \ln(R_{rs}(550))$	$R^2 = 0.86$, MAPE = 18.08, RMSE = 1.97	
					$\ln(\text{TSS}_{\text{MSI}}) = 8.318 + 1.336 * \ln(R_{rs}(550))$	$R^2 = 0.69$, MAPE = 16.67, RMSE = 3.58	
					$\ln(\text{TSI}_{\text{MSI}}) = 8.447 + 1.511 * \ln(R_{rs}(550))$	$R^2 = 0.81$, MAPE = 18.62, RMSE = 3.1	
Curuai Lake	WFI CBERS–4	TSS	9-28 mgL^{-1}	SAA	$\text{TSS} = \dfrac{293.930 * p550}{1 - (p / 0.345)} + 1.341$	$R^2 = 0.75$, MAPE = 27.08%, RMSE = 5.73 mgL^{-1}	Maciel et al. (2019)
Tapajós River	Landsat-5/ TM LISS-III	TSS	~0–120 mgL^{-1}	E	$p_{surf(Red)} = 2.64 * (TSS - 2.27)^{0.45}$	$R^2 = 0.94$, RMSE = 1.39 mgL^{-1}	Lobo et al. (2015)
Solimões River	MODIS	TSS	50–700 mgL^{-1}	E	$\text{TSS} = 759.12 * (p_{\text{nir}} / p_{\text{red}})^{1.92}$	$r = 0.89$, RMSE = 70.23 mgL^{-1}	Villar et al. (2018)
Orinoco River	Landsat-8	TSS	~25–210 mgL^{-1}	E	$\text{TSS} = 1.35512 * p_{\text{nir}} * 1000 - 2.9385$	$R^2 = 0.94$, MAPE = 19.8%, RMSE = 12.8 mgL^{-1}	Yepez et al. (2018)
Madeira River	MODIS	TSS	25–622 mgL^{-1}	E	$\text{TSS} = 1020 * (p_{\text{nir}} / p_{\text{red}})^{2.94}$	$r = 0.79$	Villar et al. (2013)
Amazon River	MODIS	TSS	7–130 mgL^{-1}	E	TSS Fraction from spectral unmixing model	RE = 10 mgL^{-1} (estimated)	Kilham & Roberts, (2011)
Amazon White water rivers	Landsat-5	TSS	0–3561 mgL^{-1}	E	Multiple regression	$R^2 = 0.76$	Montanher et al. (2014)
Madeira River	TriOS Ramses (In situ)	TSS	0–450 mgL^{-1}	SAA	Relationship between *backscattering coefficient* at 550 nm and TSS	$R^2 = 0.7345$	Bernini et al. (2019)
Amazon white water rivers	TriOS Ramses (In situ)	TSS	5–620 mgL^{-1}	E	$\text{TSS} = 20.41 * (p_{860})^{1.173}$	$R^2 = 0.89$	Martinez et al. (2015)
Amazon rivers and lakes	MODIS Terra and Aqua	TSS	0–600 mgL^{-1}	E	$\text{TSS} = \exp^{20*p_{\text{red}} + 7.68*p_{\text{nir}} + 0.31*(p_{\text{red}}/p_{\text{nir}})}$	$R^2 = 0.7$, RMSE = 75.6 mgL^{-1}	Fassoni-Andrade and Paiva (2019)
Branco and Negro rivers	Sentinel-2	TSS	0.44–22.64	E	$\text{TSS} = 881.4 * \text{R}_{\text{rs}}(660) + 2.3$	$R^2 = 0.85$	Marinho et al. (2021)

Note. OAC range refers to the minimum and maximum values; Algorithm Type (AT) refers to Empirical (E) or Semi-Analytical (SAA). In the algorithm equation column, fphy refers to phytoplankton fraction from Linear Mixture Model, R_{rs} (λ) is the RS reflectance,p (λ) is water reflectance. R^2 is the coefficient of determination, SE is the Standard Error, MSE is the mean square error, %NMSE is the normalized mean squared error, MAPE is the Mean Absolute Percentage Error, RMSE is the root mean square error, PE is the percentage error. For the equations of statistical metrics, the reader is referred to each reference.

TSS trends have been documented in the Amazon River (Martinez et al., 2009; Montanher et al., 2018) and the Madeira River (Latrubesse et al., 2017; Li et al., 2020) that might be related to dam construction (see Section 6.4 for details). The seasonal and inter-annual dynamics of suspended sediment at the Amazon River estuary were studied using 8-day composite time series (2000–2013) of MODIS Aqua and Terra satellite continental products (Gensac et al., 2016). TSS concentrations were estimated using a near-infrared band algorithm previously developed for turbid water (Martinez et al., 2009). The results provided a better understanding of mud bank formation, migration, and coast geomorphology indicating the key role of satellite data combined with in situ measurements. RS data in Amazon were also used to evaluate siltation impacts caused by artisanal gold mining in the Tapajós River basin (Lobo et al., 2015, 2016; see Section 6.4 for details). Furthermore, Fassoni-Andrade and Paiva (2019) mapped for the first time the spatial-temporal pattern of sediment in clear, white, and the black water of the Amazon rivers (Figure 8d). Despite errors in the empirical model, temporally filtered reflectance in red and infrared revealed sediment variations in rivers and lakes. Therefore, it was possible to characterize hydrological processes, such as backwater effects, overbank flow, and sediment resuspension in lakes. It was observed that depression lakes of the middle reach receive sediments-rich water by overbank flow during the flood, and resuspension of sediments occurs in the low water period, as previously documented (Bourgoin et al., 2007). In ria lakes, the main water source comes from the local basin (surface runoff and local rainfall) with river inflows adding sediment during the low water period.

One of the main challenges regarding watercolor RS is identifying and separating each constituent contribution from the water column emerging signal. The high sediment concentrations, which can mask the contributions of Chl-*a* and CDOM, make this challenge especially significant in Amazonian waters (Jorge et al., 2021). The semi-analytical approach, which has performed well in other complex waters (Gholizadeh et al., 2016; Werdell et al., 2018; Zheng & DiGiacomo, 2017), is an alternative to overcome this challenge. However, it depends on sensors with spectral, radiometric, and spatial characteristics suitable for inland waters for calibrating high-performance algorithms. Initial applications of this approach in Amazonian waters, using Landsat-8/OLI, Sentinel-2/MSI, and Sentinel-3/OLCI data, have shown promising results (Bernini et al., 2019; de Carvalho et al., 2015; Jorge et al., 2017; Maciel, Barbosa, et al., 2020). Furthermore, hyperspectral sensors missions such as NASA's Plankton, Aerosol, Cloud, ocean Ecosystem (PACE; Werdell et al., 2019) and recently launched ones such as PRISMA (Giardino et al., 2020; Niroumand-Jadidi et al., 2020) may help to overcome this challenge. Due to the extensive temporal variability in the constituent concentration, a promising approach is to integrate hybrid and semi-analytical algorithms to obtain adequate accuracy in a wide range of OACs. To cope with the frequent cloud coverage and obtain data compatible with aquatic dynamics, the concomitant use of inter-calibrated sensors data (Landsat-8/OLI, Sentinel-2/MSI, Sentinel-3/OLCI, and CBERS-4A/MUX), called the virtual constellation, can be a solution. In this sense, two ongoing initiatives are the Brazil Data Cube project (http://brazildatacube.dpi.inpe.br/portal/explore) and the Harmonized Landsat Sentinel (Claverie et al., 2018), which propose to provide intercalibrated data from different sensors. Moreover, to investigate dynamic processes in aquatic ecosystems, high spatiotemporal resolution nanosatellites represent a promising tool for understanding the short-term responses of floodplain lakes' biota to hydrological changes (Maciel, Novo, et al., 2020; Nagel et al., 2020).

All the improvements in RS technologies in the last decades have supported more accurate algorithms for suspended sediment retrieval in the Amazon. However, as demonstrated in Table 5, Chl-*a* and CDOM estimates are still a challenge in those optically complex waters. Furthermore, the accurate retrieval of Chl-*a* and CDOM is dependent on precise RS data, which demands the inversion of those OACs. In this sense, new sensors with the high radiometric and spectral resolution are imperative. Finally, more robust techniques, such as semi-analytical algorithms, machine learning approaches, and cloud computing platforms (e.g., Google Earth Engine), can improve water quality RS studies in the Amazon basin.

5. Total Water Storage and Groundwater Storage

Water mass redistribution is a key parameter needed to understand the climate system and its temporal variations at monthly to multi-decadal time-scales. Over land, it corresponds to the continuous exchange of water masses between surface (i.e., rivers, lakes, wetlands, snow cover, and mountain glaciers) and sub-surface (soil moisture and groundwater) storages, and with the atmosphere and the ocean through rainfall, evapotranspiration, and runoff. Total water storage is the sum of the water contained in the different hydrological reservoirs. The importance of surface water in the Amazon basin was presented in Section 4. Groundwater storage also plays a major role in the hydrology of the Amazon and exerts a large influence on climate variability and rainforest ecosystems (Pokhrel et al., 2013). Strong memory effects of the Amazon groundwater system propagate climate anomalies over the region for several years (Frappart et al., 2019; Miguez-Macho & Fan, 2012; Pfeffer et al., 2014).

The GRACE mission, in operation from March 2002 to June 2017, and the GRACE Follow-On mission (GRACE FO), in orbit since May 2018, enable the monitoring of the spatio-temporal changes of Terrestrial Water Storage (TWS; Tapley et al., 2004). Its temporal anomaly is derived from GRACE observations which measure the very small variations in the Earth's gravity field (Tapley et al., 2004). GRACE-derived TWS Anomaly (TWSA) observations, in spite of their coarse spatial resolution of ∼200–300 km, have been widely used to analyze the impact of climate variability and global changes on the water masses redistribution over land (Tapley et al., 2019), and groundwater storages in combination with external observations (Frappart & Ramillien, 2018).

Over the whole Amazon basin, GRACE-derived TWS annual amplitude was found to range from 300 to 450 mm (Figure 9; Chen et al., 2009; Crowley et al., 2008; Frappart, Seoane, & Ramillien, 2013; Xavier et al., 2010). This range corresponds to twice the annual amplitude of surface water storage of the whole basin (Frappart et al., 2012; Ndehedehe & Ferreira, 2020), meaning that the annual amplitude of the subsurface storage variations (soil moisture and groundwater) also represents half of the TWS annual amplitude. Large variations of this value were observed among the major Amazon sub-basins depending on the extent of floodplains (Frappart et al., 2011, 2019; Papa et al., 2013). Rainfall and GRACE-based TWSA were found to be highly correlated in the Amazon and its major sub-basins (over 2003–2010), even at interannual timescales with Pearson's correlation coefficients generally higher than 0.7 (except in the basins located in the Andes) with a time-lag varying from 0 to 3 months (Frappart, Ramillien, & Ronchail, 2013; Ndehedehe & Ferreira, 2020). Similar results were obtained between TWSA and river discharges over the same time spans (Frappart, Ramillien, & Ronchail, 2013). Good agreement was also observed between TWS and satellite-derived surface water extent (from GIEMS), rainfall, and discharge over various time-span (Papa et al., 2008; Prigent et al., 2007, 2012; Tourian et al., 2018). These studies revealed the complexity of water transport among the different sub-basins of the Amazon with the presence of hysteresis in the relationship between surface water extent and TWSA.

The analysis of the spatio-temporal patterns of TWS changes provided new information on the impact of the extreme climate events (exceptional droughts and floods which occurred in 2005, 2010, 2012–2015, and 2009, 2012, respectively) on land water storage in the whole Amazon basin or in its major sub-basins (Chen et al., 2009, 2010; Espinoza et al., 2013; Ferreira et al., 2018; Frappart, Ramillien, & Ronchail, 2013). Examples of maps of difference in TWSA between a given month and its climatological mean are presented in Figures 9a and 9b for May 2009, and October 2010, respectively. These months were chosen as they correspond to the extremum of these climate events (droughts of 2005, 2010, and 2015, flood of 2009). This information has been revealed to be complementary to what can be obtained using spatialized rainfall and in situ water levels and discharges. For instance, the patterns of minimum TWSA during the droughts of 2005 and 2010 were found to be in good coincidence across the basin with the areas with large fire activity (Aragão et al., 2008; Zeng et al., 2008) and of considerable tree mortality (Phillips et al., 2009) as reported in Frappart, Ramillien, and Ronchail (2013). TWSA also helped, jointly with hydrological modeling, to characterize the recent extreme droughts which occurred in the Amazon, highlighting the importance of the interactions between subsurface and surface water storages to mitigate the deficit in surface reservoirs (Chaudhari et al., 2019).

A direct approach to estimate GW storage anomalies is to remove the contribution of the different hydrological compartments from GRACE-based TWSA as follows:

$$\Delta GW = \Delta TWS - \Delta SW - \Delta SM - \Delta CW - \Delta SWE \tag{1}$$

where Δ represents the anomaly of water storage in the different hydrological compartments, SW is the surface water storage, SM is the soil moisture or water contained in the root zone, CW is the water contained in the canopy, and SWE is the snow water equivalent. This latter term was neglected in the studies performed

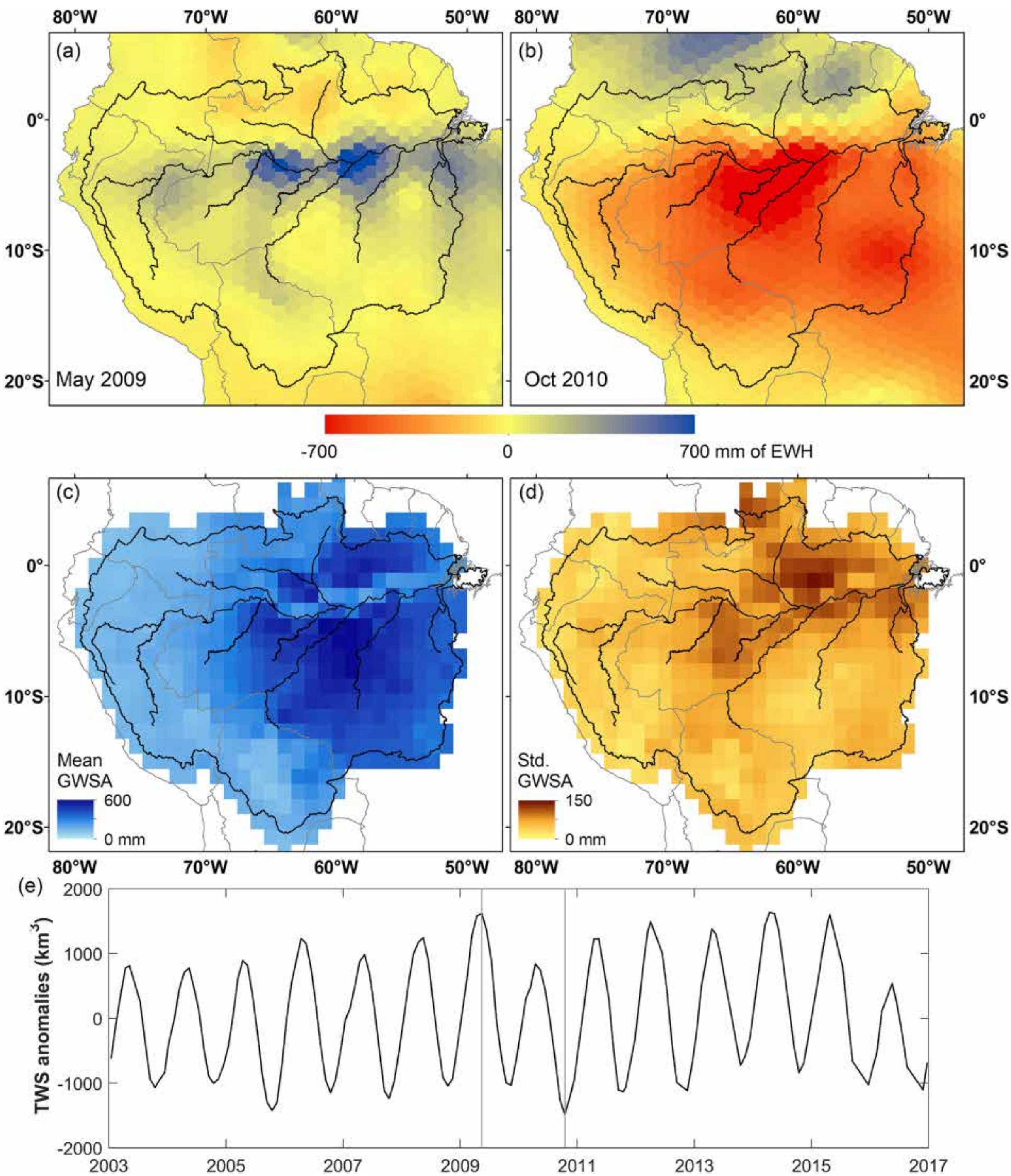

Figure 9. Maps of TWSA during two extreme events (a) The flood in May 2009, and (b) The drought in October 2010. Mean annual changes in groundwater storage anomaly - (c) GWSA and (d) associated standard deviation over 2003–2010 (adapted from Frappart et al., 2019). (e) Time series of GRACE-based TWSA (km^3) over the Amazon basin between 2003 and 2016. The vertical lines show the months of maximum (May 2009) and minimum (October 2010) values.

in the Amazon basin as no reliable information on this water storage was available. In most cases, water from the other compartments (SW and SM) is provided by model outputs and/or in situ measurements. For Amazon, it is necessary to accurately take into account the SW component as it represents around half of the TWSA (Frappart et al., 2012, 2019). Using external information from hydrological models for SW, SM, and CW, groundwater storage anomalies were estimated over 2003–2015, revealing a strong link between geological properties and GW storage: the largest groundwater storage capacity in Brazil was found in regions with the highest permeability of the rock layers (e.g., the Guarani and Alter do Chão aquifers; Hu et al., 2017). But in these cases, SW storage was limited to river storage, neglecting the storage in the extensive floodplains of the Amazon basin. In order to adequately take into account the contribution of SW components, methodologies were developed to estimate SW storage variations from RS observations (Frappart et al., 2008, 2012; Ndehedehe & Ferreira, 2020). SW storage anomalies were obtained by combining surface water extent (generally from GIEMS, see Section 4.2) and altimetry-based time series of water levels (see Section 4.1) over rivers and floodplains. Frappart et al. (2012) estimated the monthly variations of SW storage at the basin scale during the 2005 drought and found that the amount of water stored in the river and floodplains of Amazon during this extreme event was 130 km^3 (70%) below its 2003–2007 average, representing almost a half of the anomaly of minimum TWS as estimated by GRACE.

Using this newly external information on SW storage variations, along with SM storage estimates from hydrological models, GW storage anomalies were first estimated over 2003–2004 in the Negro River Basin, one of the largest tributaries to the Amazon basin (Frappart et al., 2011). The spatial pattern of the annual amplitude of GW anomalies agrees well with the regional hydrogeological maps and the amplitude are consistent with observations of water level at local wells and altimetry-based time series of water levels in two adjacent wetlands where the groundwater table reaches the surface during the whole hydrological cycle (Frappart et al., 2011).

This approach was then extended to the whole Amazon basin over 2003–2010, using about 1000 ENVISAT RA-2 altimetry VSs of surface water elevation (Frappart et al., 2019). SW storage over the entire basin had an annual amplitude ranging between 900 and 1,300 km^3 (Frappart et al., 2012). GW estimates had good agreement with scarce in situ groundwater observations and low-water maps of the GW table (Frappart et al., 2008). At basin-scale, the results have realistic spatial patterns when compared to hydrogeological maps of Brazil (e.g., porosity maps, aquifer boundaries, GW recharge). The seasonal amplitude of GW was estimated to contribute between 20% and 35% of the GRACE-derived TWS amplitude in the Amazon basin(-Frappart et al., 2019). The impact of the 2005 extreme drought on GW storage was also observed and lasted several years (Frappart et al., 2019).

Radar altimetry was used to estimate low-water maps of the GW table in the central part of the Amazon basin (Frappart et al., 2008). Owing to the connection between surface and groundwater during the low water period in the alluvial plains of the central Amazon (54°–70°W, 0°–5°S), annual lower water levels of 593 altimetry VSs were interpolated to generate yearly maps of groundwater base level (GWBL) between 2003 and 2009. The results show that GWBL is governed by the surface topography and that several years were needed for GWBL to recover from the extreme drought of 2005 (Pfeffer et al., 2014).

The recent launch of the GRACE Follow-On (GRACE-FO) offers an opportunity to extend the monitoring of TWS and GWS changes after 2018. Despite a lack of data between October 2017 (end of GRACE operation) and May 2018 (launch of GRACE-FO), two decades of TWSA will be soon available, allowing analysis of the impact of multi-year climatic events such as ENSO on land and ground water storages. The major drawbacks of these data are their low spatial (~200 km) and temporal (1 month) resolutions which are not sufficient to study the dynamics of fast hydrological events. To overcome these drawbacks, the GRACE-FO payload contains advanced versions of the sensors present on-board GRACE and a novel laser ranging interferometer (LRI), measuring the satellite-to-satellite distance in parallel with the K-band radar instrument. The LRI is expected to be 26-times more accurate than the K-band radar instrumentation on-board GRACE (Tapley et al., 2019). This better-expected accuracy is likely to improve the quality and the spatial resolution of the retrieved TWSA. New approaches based on the use of Kalman filter were developed to increase the TWSA temporal resolution to quasi-daily without degrading the spatial resolution (Ramillien et al., 2015, 2020).

6. Integrative and Interdisciplinary Studies

RS data have provided breakthrough advances in the understanding of the Amazon's hydrology and associated aquatic environments. In Sections 2–5, we have presented and discussed scientific advances for individual components. In this Section, we introduce research agendas that have benefited from the integration of observations from multiple components of the Amazon water cycle. These include the computation of the water budget (Section 6.1), application of hydrological models (Section 6.2), understanding of aquatic ecosystems (Section 6.3), and past and ongoing environmental changes over the Amazon basin (Section 6.4).

6.1. Water Budget

In order to better understand the complex hydrological processes in the Amazon basin, it is necessary to monitor each component of the water cycle and to understand how these components link and interact. Thus, studying the Amazon basin water budget (WB) requires the use of a large variety of observations, especially because the basin includes complex local environments (e.g., floodplains) and processes (e.g., soil moisture and canopy transpiration) that are difficult to characterize by satellite observations.

Among the WB literature, the Amazon basin has been one major region among global analyses of the water cycle (Munier & Aires, 2018; Pan et al., 2012; Sahoo et al., 2011; Zhang et al., 2018) or the main focus of the analysis (Azarderakhsh et al., 2011; Builes-Jaramillo & Poveda, 2018; Moreira et al., 2019; Oliveira et al., 2014). Most WB studies used only one satellite product for each water component (Azarderakhsh et al., 2011; Builes-Jaramillo & Poveda, 2018; Maeda et al., 2015; Moreira et al., 2019; Oliveira et al., 2014; Rodell et al., 2011). The use of a multiplicity of the satellite products for each water component can reduce uncertainties, through an approach that is based on observations only (Aires, 2014) or integrating model simulations and re-analyses (Pan et al., 2012; Zhang et al., 2018).

Continuous quality improvement and increased use of satellite products, associated with more sophisticated integration techniques, have allowed better characterization of the water cycle. WB analyses have been used to (a) directly estimate a missing water component such as ET (Maeda et al., 2017; Rodell et al., 2011), R (Azarderakhsh et al., 2011; Oliveira et al., 2014), and terrestrial water storage change dS (Moreira et al., 2019), (b) diagnose the hydrological coherence of a combination of RS-based estimates and investigating discrepancies (Builes-Jaramillo & Poveda, 2018; Moreira et al., 2019; Oliveira et al., 2014), and (c) to optimize RS-based estimates to obtain a hydrologically coherent water cycle (Munier & Aires, 2018; Pan et al., 2012; Pan & Wood, 2006; Pellet et al., 2021; Sahoo et al., 2011). The three main uses of WB closure are detailed in the following paragraphs.

When estimating missing water components, the objective can be to investigate seasonal patterns (Azarderakhsh et al., 2011; Moreira et al., 2019) and more complex features such as trends and impacts due to land use and land cover changes (Oliveira et al., 2014). The studies provide uncertainties for their estimates based on the relative uncertainties of the other components (Rodell et al., 2011). When focusing on ET, the literature stresses that ET is controlled by both P and radiation without being limited by one of these two (Maeda et al., 2017); but the seasonality remains unclear due to large uncertainty P. Nevertheless, the indirect estimation ET has been used by Rodell et al. (2011) to evaluate model ET outputs over the Tocantins basin and the authors concluded that much effort is still required on the ET modeling.

Diagnosing WB coherency by combining RS products is a useful tool to assess the quality of the RS products. For instance, Moreira et al. (2019) demonstrated that the MSWEP and GLEAM data sets reduce the WB imbalance. Oliveira et al. (2014) showed that recent versions of the TMPA also improve WB closure compared to older versions. Builes-Jaramillo and Poveda (2018) have jointly evaluated the surface and atmospheric water balances over the Amazon, and their diagnostic of the discrepancy between various ET estimates showed that RS-based ET products balance better the WB than the model and reanalysis outputs. As reported in Builes-Jaramillo and Poveda (2018) and Moreira et al. (2019), the WB imbalance relates at sub-basin to the drainage area and the climatic conditions (i.e., tropical or mountainous) which impact the signal-to-noise ratio of each water component.

Several studies have used the WB closure as a constraint for the optimization of satellite estimates, jointly for each water component. Pan and Wood (2006) developed an optimization of the satellite products using an assimilation scheme within a land surface model at the basin scale. This method has then been applied to the Amazon basin (Pan et al., 2012; Sahoo et al., 2011). Zhang et al. (2018) extended this scheme to the pixel scale by considering only simulated R. Similarly, Aires (2014) described several approaches to integrate satellite observation (simple weighting, optimal interpolation, post-filtering, and neural networks) with the WB closure constraint but without the use of surface or hydrological models to obtain an

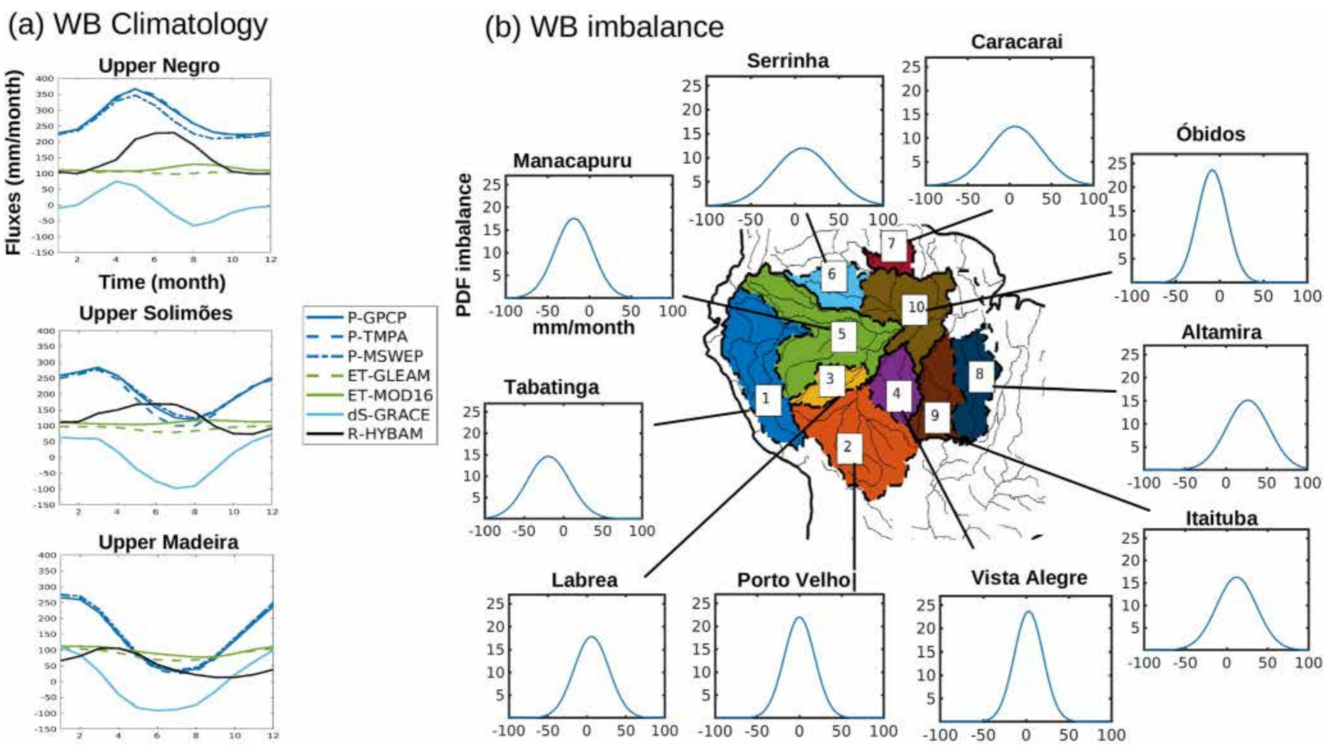

Figure 10. (a) Seasonal climatology of all the water components: precipitation (*P*), evapotranspiration (ET), water storage change (*dS*), and discharge measured at in situ gauges (*R*) described by one or multiple data sets. (b) Probability Density Function (PDF) of the resulting WB imbalances are shown at the sub-basin scale (right). PDF provides the bias and variance of the imbalance.

observational database. Munier and Aires (2018) investigated Amazon hydrology using this framework, and Pellet et al. (2021) added inter-basins constraints on the budget closure using river discharges over several stations in the basin. This technical framework allows for the optimization of the satellite data sets and can be used to develop new tools in hydrology such as the assimilation of GRACE data (Zhang et al., 2018). For instance, in Pellet et al. (2021), the spatial patterns of *P*, ET and *dS* were used to estimate the river discharge along the river network.

The estimation of the uncertainty of each water component is one of the main objectives of a WB analysis. Such characterizations are generally component- and site-specific. For instance, Moreira et al. (2019) extensively evaluated the satellite estimate uncertainty of *P* and ET using in situ data (i.e., 300 precipitation gauges and fourteen eddy-covariance monitoring sites), however, this approach is limited due to the sparsity of the observation network. Sahoo et al. (2011) used the distance to non-satellite estimate while Zhang et al. (2018) and Pellet et al. (2021) used the spread of the satellite as a proxy for uncertainty. Azarderakhsh et al. (2011) or Munier and Aires (2018) used a literature review based on RS expertize to quantify the uncertainties of the satellite products. Studies generally assume a value of 5%–10% of error for *R* while *dS* errors from GRACE are often computed following the specifications for leakage and measurement covariance errors (Rodell et al., 2004). All the studies agree on the relatively high contribution of the *P* estimate in the total WB imbalance (∼40%). Moreira et al. (2019) and Oliveira et al. (2014) found a positive bias *P* when comparing them to in situ data, but all the integration approaches (Pan et al., 2012; Pellet et al., 2021; Sahoo et al., 2011) result in an increased *P* estimate. Furthermore, Moreira et al. (2019) considered that *dS* is the second contributor to the WB imbalance (∼25%) while Sahoo et al. (2011) and Pellet et al. (2021) found a higher contribution from ET (∼30%). All the optimization strategies have shown that the WB can be balanced within the range of the RS-based uncertainties.

Figure 10a represents the climatology of the four water components in three basins and using several data sets for each water component. The three basins are: northern Negro catchment upstream of the Serrinha station, the central basin upstream of the Manacapuru station (including the drainage area upstream of the

Tabatinga station), and the southern basin upstream of the Fazenda (Fz) Vista Alegre station (including the drainage area upstream of Porto-Velho station). The climatological season (i.e., annual cycle) of all the water components is represented in mm/month. All satellite products have bias and uncertainties, but this multi-component analysis can isolate the spatial patterns over the Amazon basin. For instance, the annual cycles of the WB differ on the northern and southern basins. As reported in the literature (Espinoza, Sörensson, et al., 2019; Marengo, 2005), over southern basin, *P* is driven by the monsoon with a peak in January and has larger seasonal variations (e.g., min-max range) and lower annual average than on the northern basin, where *P* peaks in May. The *P* seasonality drives *R* over all basins (north and south) with a time-lag of 1–2 months. Over the central-western basin, *R* can be higher than *P* for a particular month, and the *P*-*R* peak is about 4 months related to the runoff and river discharge travel times inside the basin (Sorribas et al., 2020). *dS* is in phase with *P* in the southern basin, but shows a particular season over the Negro and Branco basins: *dS* is equal to zero during the dry season and a linear transition exists between maximum and minimum. Over these basins, *dS* become negative while *R* was increasing, and reached its maximum 2 months later. This illustrates the effect of water storage in floodplain before releasing it into the river. ET seasonal variation is weaker but the ET peak seems to be in phase with *P* over the southern basin arguing for a water-limited behavior while the ET peak follows the *P* minimum month in the northern basin of an energy-limited system (Maeda et al., 2017). In Pellet et al. (2021), the correction ET based on the closure of the water cycle enhances the water limitation regime over the central Amazon basin and the energy limitation over the northern Amazon. In the south, during dry months (JJA), ET is higher than *P*, and water that evaporates is provided by the soil storage which continues to lose water until November. For this season, the role of ET on the water cycle is relatively more important in the dry season than in the rainy season (Marengo, 2005).

To investigate the overall WB imbalance related to the bias and uncertainty of all the water components, Figure 10b shows the Probability Density Function (PDF) of these imbalances at sub-basins scale. Spatially, there is a gradient in the mean of the PDF between the western and southern sub-basins. Western sub-basins have a lack of water (negative bias in the PDF), while southern sub-basins have an excess of water (positive bias). This gradient was reported by Builes-Jaramillo and Poveda (2018). Furthermore, the variance of the WB imbalance increases from south to north with the annual mean of P suggesting that a large part of the imbalance is due to *P* (Moreira et al., 2019; Pellet et al., 2021). The optimization strategy based on the closure of the WB leads to a bigger correction of the water component over western and central sub-basins (Pellet et al., 2021).

The remaining precipitation uncertainties of the globally calibrated satellite products are mainly due to the increase of the precipitation measurement errors by satellite products during the rainy season, and the lack of in situ gauges used in calibration (Moreira et al., 2019). The Amazon hydrology could benefit from the use of a dedicated network of precipitation gauges such as HYBAM Observatory Precipitation (Espinoza Villar, Ronchail, et al., 2009; Guimberteau et al., 2012) to obtain a regionally-calibrated satellite product for precipitation. Its gauges density over the Amazon basin is higher than the global gridded rainfall data set generally used to calibrate satellite products (Guimberteau et al., 2012).

Estimating ET in the Amazon basin remains a challenge (see Section 3). In Figure 10, the use of different ET data sets can lead to a difference of 30–50 mm/month which represents up to 50% of the ET value. Following Moreira et al. (2019), the establishment of generic methods for estimating uncertainties is of importance for improving our understanding of the terrestrial water cycle. As for *P*, one source of the improvement will be the extensive use and increase of an eddy covariance network to better understand the uncertainties in ET models.

One technical improvement in the WB-based optimization approach might come with the spatial resolution of the analysis. WB analysis has been mostly done at the basin scale over the basin (Munier & Aires, 2018; Sahoo et al., 2011) even if several studies have been conducted in sub-basins defined by river discharge stations (Azarderakhsh et al., 2011; Pellet et al., 2021). Using topography information, it should be possible to consider the runoff over land and downscale the satellite products while closing the WB at a pixel level. The satellite data sets could even be downscaled temporally to obtain a better time resolution.

As discussed in Section 5, attempts have been made to decompose the TWS from GRACE into its surface (Frappart et al., 2012; Papa et al., 2013) and groundwater (Frappart et al., 2019) components. Such decomposition could also be attempted within a full terrestrial WB analysis, especially when reliable soil moisture satellite estimates over the Amazon will become available. As mentioned in Section 4, long-term surface water data sets would also be necessary (Aires et al., 2017; Parrens et al., 2019; Prigent et al., 2020).

The GRACE-FO mission launched in 2018, the extension of the TRMM data record with the GPM mission, and the launch of the SWOT mission will provide a comprehensive set of new observations. The continuity of these satellite missions monitoring the water components is mandatory to improve our understanding of spatial hydrology patterns through more precise WB analyses and assess potential long-term trends.

6.2. Modeling the Amazon Water Cycle and Its Wetlands

Hydrologic and hydraulic models represent the water cycle storages and fluxes through a set of mathematical equations. Such process-based models are suitable tools to understand Amazon hydrological processes such as river-floodplain water exchange and groundwater-surface water interactions (Miguez-Macho & Fan, 2012; Paiva, Buarque, et al., 2013) and past floods and droughts (Correa et al., 2017), to estimate variables in ungauged regions (e.g., distributed river discharge for the last century; Wongchuig et al., 2019), and to perform scenarios of hydrological alteration due to deforestation, flow regulation by reservoirs, and climate change (Arias et al., 2020; Guimberteau et al., 2017; Júnior et al., 2015; Lima et al., 2014; Mohor et al., 2015; Pokhrel et al., 2014; Pontes et al., 2019; Sorribas et al., 2016; Zulkafli et al., 2016).

During the last decades, many models have been applied in the Amazon at different scales, from reach (i.e., more detailed studies addressing a few kilometers long river-floodplain area) to the whole basin scale. Because of the basin's remoteness and vast dimensions, RS data sets are usually adopted as either forcing (e.g., precipitation), a priori information to estimate parameter values (e.g., topographic data), validation, or calibration/assimilation data (e.g., discharge, river water levels). A major distinction can be made between (a) hydrological models that simulate vertical processes as evapotranspiration, soil water infiltration, and runoff generation mechanisms and (b) hydraulic models of surface waters, which represent flow propagation along rivers and floodplains with physically-based equations and allow the computation of variables such as surface water elevation and slope, river discharge, and surface water extent and storage sizes the differences between the two approaches.

The first generation of models in the Amazon involved the development of large-scale hydrological models, starting with the studies by Vörösmarty et al. (1989), Costa and Foley (1997), and Coe et al. (2002). With the advent of RS data sets and higher computational capacity, several models have been developed, improving the physical representation of hydrological processes, increasing the model spatial resolution, and moving from monthly to daily estimates (Beighley et al., 2009; Coe et al., 2008; Luo et al., 2017; Miguez-Macho & Fan, 2012; Paiva, Buarque, et al., 2013). These models usually adopt the following RS-based input data: precipitation with the TMPA product (Collischonn et al., 2008; Getirana et al., 2012; Zubieta et al., 2015), and more recently GPM-IMERG (Zubieta et al., 2017) and MSWEP (Beck, Van Dijk, et al., 2017); landscape properties including terrain lengths and slopes, based on DEMs (most studies using SRTM DEM); and land use and vegetation maps (global maps as FAO, or regional ones as the Brazilian RadamBrasil soil maps). The most common validation data sets from RS are water level from satellite altimetry (Section 4.1), surface water extent (Section 4.2), and total water storage (Section 5).

These model applications deepened our comprehension of the water partition between soil, surface water, and groundwater, and acted as laboratories to improve global hydrological models, which in turn are fundamental elements of Earth System models. The assessment of land surface and global hydrological and hydrodynamic models in the Amazon has been a standard procedure in geoscientific model development and in model intercomparison projects (Alkama et al., 2010; Decharme et al., 2008; Getirana et al., 2012, 2014; Getirana, Peters-Lidard, et al., 2017; Guimberteau et al., 2014, 2017; Pilotto et al., 2015; Towner et al., 2019; Yamazaki, Baugh, et al., 2012; Yamazaki et al., 2011; Zulkafli et al., 2013). At the basin scale, the fraction of the total water storage corresponding to surface waters was estimated as 56%, 41%, and 27% by Paiva, Buarque, et al. (2013), Getirana, Peters-Lidard, et al. (2017); Getirana, Kumar, et al. (2017) and Pokhrel et al. (2013), respectively. These values have been compared to RS-based estimates (Frappart et al., 2012, 2019; Papa et al., 2013). Furthermore, basin-scale average ET estimated as 2.39–3.26 mm/day by an ensemble of land surface models (Getirana et al., 2014), and as 2.72 mm/day by Paiva, Buarque, et al. (2013), were slightly lower than values by basin-scale RS (Pacada et al., 2019) and an in situ eddy-covariance networks (Costa et al., 2010), which estimated values of 3.11–3.58 mm/day across a gradient from southern dry to equatorial wet Amazon forests. The role of soil water storage to sustain dry season ET in the Amazon was shown by modeling experiments at local (Fang et al., 2017) and basin scale (Getirana et al., 2014). Some studies addressed the role of groundwater and soil storage on the water balance, and the importance of its representation into hydrological models. Applications at headwater basins showed the predominance of groundwater on headwater water storage (Cuartas et al., 2012; Niu et al., 2017), in agreement with in situ monitoring studies (Hodnett et al., 1997). Miguez-Macho and Fan (2012) suggested the same pattern at the whole basin scale. Their model also indicated important two-way feedback between floodwater and groundwater, and the existence of large areas not subject to surface flooding across the basin, but where a high water table level would be responsible for keeping high soil water content year-round. The simulation of multiple soil layers in the ORCHIDEE land surface model, in contrast to a simple 2-layer "bucket" model, was also shown to improve the representation of the soil water dynamics and the total water storage in the Amazon, especially for the drier regions in the southern sub-basins (Guimberteau et al., 2014).

Among hydraulic models of surface waters, a pioneer study by Wilson et al. (2007) is one of the first hydraulic modeling experiments performed over large domains, which later prompted the development of many global hydrodynamic model applications (Bates et al., 2018). The authors applied the LISFLOOD-FP model to a 260 km reach of the Solimões River and estimated the river-floodplain water exchange as at least 40% of the river volume in that reach. For a relatively different reach in the Central Amazon (from São Paulo de Olivença to Óbidos), Richey et al. (1989) estimated this ratio as 30% based on a simpler routing method, while Sorribas et al. (2020) estimated a value of 40% for the Amazon system, based on large scale hydraulic modeling (see below). The authors also found the model accuracy to be higher for the high water period, as has been also reported by recent studies (Pinel et al., 2019; Rudorff et al., 2014a), likely due to misrepresentation of the terrain heterogeneities and small disconnected lakes during the dry season. Furthermore, since the river-floodplain water exchange often occurs through floodplain channels and breached levees that hinder its conceptualization as a simple overbanking flow (Trigg et al., 2012), hydraulic models have the challenge to estimate effective channel parameters that represent these complex processes (Fleischmann et al., 2018; Trigg et al., 2009). Recent efforts have been addressing this topic, considering for instance the incorporation into models of different cross section shapes (Neal et al., 2015) as well as assimilation of satellite altimetry to infer bathymetry (Brêda et al., 2019; Garambois et al., 2020; Pujol et al., 2020). Other applications at reach or floodplain lake scale were developed by Bonnet et al. (2008, 2017), Ji et al. (2019), Trigg et al. (2009), and Wilson et al. (2007), and addressed the relative role of local runoff and river inflow as the main water input, ranging from local runoff-dominated systems in the Lago Calado (Ji et al., 2019; Lesack & Melack, 1995) to river-dominated ones in the Curuai (Figure 11d) and Janauacá systems (Bonnet et al., 2008, 2017; Pinel et al., 2019; Rudorff et al., 2014a, 2014b), through either channelized or diffuse flow patterns. In the case of Curuai and Janauacá, the Amazon or Solimões river was responsible for 82% and 93% of the floodplain annual influxes, respectively (Bonnet et al., 2017; Rudorff et al., 2014b).

The first basin-scale inundation model was introduced by Coe et al. (2002), and numerous hydrologic models were developed and coupled to inundation schemes afterward (Coe et al., 2008; Getirana et al., 2012; Getirana, Peters-Lidard, et al., 2017; Hoch et al., 2016; Luo et al., 2017; Miguez-Macho & Fan, 2012; Paiva, Buarque, et al., 2013; Yamazaki, Lee, et al., 2012; Yamazaki et al., 2011). The models featured varying degrees of physics representation, with the simulation of floodplains moving from simple storage components to dynamic hydraulic schemes, which can represent relevant processes such as backwater effects. For hydraulic models, additional RS-based information required as input data includes river channel geometry as width, and floodplain topography from DEMs (mainly SRTM and its derivatives with vegetation removal to represent the bare terrain; see Baugh et al. (2013), O'Loughlin et al. (2016), Yamazaki et al. (2019) and Fassoni-Andrade, Paiva, Rudorff, et al. (2020). For local scale hydraulic models, additional parameterization usually involves the definition of floodplain roughness based on land cover maps (Pinel et al., 2019; Rudorff et al., 2014a). RS validation data sets are typically surface water elevation and surface water extent (Hall et al., 2011; Schumann et al., 2009).

These hydraulic model applications revealed the combination of backwater effects and floodplain storage to drive the flood wave behavior along Amazon rivers (Paiva, Buarque, et al., 2013), causing strong attenuation

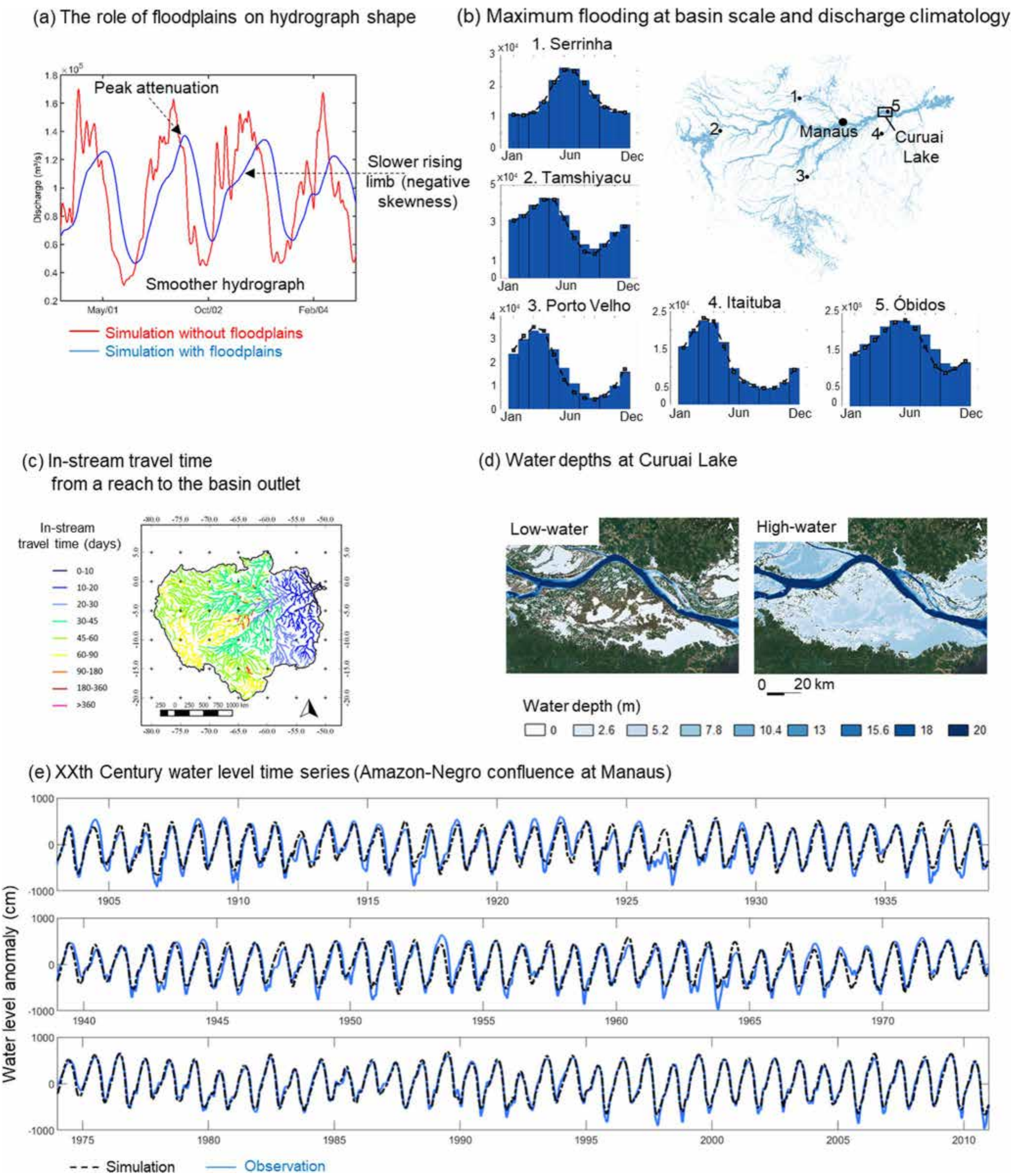

Figure 11. Recent applications of hydrologic and hydraulic models in the Amazon basin have added insights into the role of river floodplains on (a) Hydrograph shape (Fleischmann et al., 2016) and (c) In-stream travel times (Sorribas et al., 2020), and provided the estimation of (b) Long-term discharge climatology (Paiva, Buarque, et al., 2013), (c) Long-term water level time series (example for the location of Manaus; Wongchuig et al., 2019), and (d) Floodplain water depths (example for the Curuai Lake, 2014 high and low water seasons; Rudorff et al., 2014a).

Table 6
Summary of Main Differences Between Hydrologic and Hydraulic Models of Surface Waters, With Examples of Model Applications in the Amazon Basin

	Hydrological models	Hydraulic models of surface waters
Main simulated process	Vertical processes (e.g., evapotranspiration, soil water infiltration, and runoff generation mechanisms) and groundwater dynamics	River-floodplain interaction (e.g., floodplain storage, backwater effects)
Main forcing (boundary conditions)	Precipitation	River discharge, river water level, and precipitation
Main output variables	Water balance, evapotranspiration, soil water, and groundwater storage, river discharges	Inundation maps, river-floodplain water depths, longitudinal water levels along rivers, river discharges
Typical scientific outcomes	Quantification of water balance components, water storage partition between surface and subsurface reservoirs, evapotranspiration dynamics, impacts of human alteration on water balance components (e.g., changes in precipitation partition into ET and runoff)	Floodplain water storage and residence time, water travel times across river-floodplain systems, rating curves (water level-discharge relationships) for operational use, impacts of human alteration on flood dynamics
Examples of studies	Beighley et al. (2009);, Coe et al. (2002); Costa and Foley (1997); Cuartas et al. (2012); Miguez-Macho and Fan (2012); Paiva, Buarque, et al. (2013); Vörösmarty et al. (1989)	Fleischmann et al. (2020); Garambois et al. (2017); Getirana et al. (2012); Miguez-Macho and Fan (2012); Paiva, Buarque, et al. (2013); Paris et al. (2016); Pinel et al. (2019); Rudorff et al. (2014a); Sorribas et al. (2020); Trigg et al. (2009); Wilson et al. (2007); Yamazaki, Lee, et al. (2012)

Note. Some examples are provided in both categories since they refer to hydrologic-hydraulic models.

and delay up to 2.5 months. Floodplain storage is also responsible for the general negative hydrograph skewness in the main Amazon rivers, with a slower rising and a faster falling limb (Fleischmann et al., 2016, Figure 11a). Sorribas et al. (2020) used particle tracking methods to estimate surface water travel times along the Amazon basin as 45 days (median), with 20% of Amazon River waters flowing through floodplains (Figure 11c). While basin-scale applications have employed 1D models (longitudinal direction along rivers), the necessity of representing the 2D diffuse flow in floodplains, especially during receding waters, was highlighted by Alsdorf et al. (2005), who combined interferometry data with a simple continuity-based model to show that floodplain storage changes decrease with distance from the main channel. Generally, the water level in the river-floodplain system is not horizontal, and the river-floodplain is not homogeneously mixed (Alsdorf et al., 2007), as assumed by several 1D models. While a proper characterization of the complex river-floodplain interactions with hydraulic models has been done at local scales (Pinel et al., 2019; Rudorff et al., 2014a), it is still to be developed for the regional scale—for instance, to be able to infer hyperresolution (e.g., 30 m spatial resolution) flooding patterns for the whole central Amazon at weekly to monthly resolution. Finally, the full coupling between hydrologic and hydraulic models has been suggested to improve the representation of the floodplain-upland interactions, for instance through a more proper representation of open water evaporation in flooded areas (Getirana, Kumar, et al., 2017). However, recent studies have suggested that this process has a relatively low impact on the total ET estimates because of the general energy-limited (and not water-limited) ET in the Amazon (Fleischmann et al., 2020; Paiva, Buarque, et al., 2013). A different conclusion is expected for semi-arid wetlands (Fleischmann et al., 2018).

Regional scale validation of inundation models has been done with surface water extent (Getirana et al., 2012; Luo et al., 2017; Paiva, Collischonn, et al., 2013; Wilson et al., 2007; Yamazaki et al., 2011) based on the products by Hess et al. (2003), GIEMS from Prigent et al. (2007), and more recently with the SWAF database (Parrens et al., 2017) (see Section 4.2 for a description of these products). Although the flooding seasonal cycle is usually well captured by most models, estimates usually diverge in terms of magnitude (Fleischmann et al., 2020), and the fusion between different techniques is likely the optimal solution. However, more detailed validation experiments, for instance with maps based on SAR data, are needed, although many SAR data classifications were already developed for individual Amazon wetlands (Section 4.2). A recent application used ALOS/PALSAR imagery for a local scale model validation in the Janauacá floodplain system (Pinel et al., 2019).

Regarding surface water elevation, hydraulic models are typically capable of representing anomalies satisfactorily. Estimates of absolute values, however, are usually less accurate (Fleischmann et al., 2019), although good results have been achieved (Wilson et al., 2007). The hundreds of virtual stations available (see Section 4.1) have provided breakthrough improvements of modeling systems, especially in terms of distributed model validation with dozens of virtual stations (Fleischmann et al., 2020; Getirana, Peters-Lidard, et al., 2017; Paiva, Buarque, et al., 2013) and recent model calibration and assimilation (Brêda et al., 2019; Oliveira et al., 2021). Validation exercises yielded Nash-Sutcliffe coefficients higher than 0.6 for 60% of the 212 ENVISAT virtual stations assessed by Paiva, Buarque, et al. (2013), and amplitude errors lower than 0.8 m and absolute bias lower than 2.3 m for most of the stations analyzed by Yamazaki, Lee, et al. (2012). The combination of satellite altimetry with a hydraulic model for an ungauged reach of the Xingu River led Garambois et al. (2017) to propose the concept of hydraulic visibility through RS data sets, that is, the capability of current and future satellite altimetry data to properly estimate river hydraulic variables. Altimetry data were shown to be relevant for the understanding of the hydraulic functioning of ungauged braided reaches in Amazonian rivers, especially along stretches with heterogeneous bed morphology and strong downstream control, which have major effects on surface water elevation and slope (Birkett et al., 2002).

The main output variables that have been addressed by hydrologic-hydraulic models are ET, soil water storage, river discharge, surface water elevation, and surface water extent. However, other variables are also important for an effective understanding of the water cycle and need to be better constrained within modeling systems. For instance, only a few studies have addressed simulated water velocity (Dias et al., 2011; Fassoni-Andrade, 2020; Pinel et al., 2019) and flood storage (Fleischmann et al., 2020; Getirana, Kumar, et al., 2017; Paiva, Buarque, et al., 2013) in the Amazon wetlands, which are fundamental variables to understand flood dynamics, even though the latter (flood storage) was already estimated by different RS methods (see Section 5).

As there are still uncertainties in both models and RS estimates, model calibration, and data assimilation (DA) techniques have been developed to improve model predictability, based on the optimal combination/analysis of these two. Model calibration was performed with satellite altimetry by Getirana et al. (2013) andOliveira et al. (2021), showing the benefits of using such data sets toward model general improvement in terms of discharge estimation. In turn, the evaluation of DA techniques (mainly the Kalman Filter-based methods) within the Amazon involved many experiments with RS data (e.g., satellite altimetry), from reach to regional scale (Brêda et al., 2019; Emery et al., 2018; Garambois et al., 2017; Paiva, Collischonn, et al., 2013). These studies showed the applicability of such methods to improve model estimates and representation of the water cycle in general. The usefulness of DA schemes for better estimating discharges was demonstrated for forecasting (Paiva, Collischonn, et al., 2013), comprehension of past extreme events (Wongchuig et al., 2019), and near-real-time discharge estimation (Paris et al., 2016). The study by Wongchuig et al. (2019) was the first to show discharge estimation in a spatially distributed way for the last 100 years (Figure 11e), estimating extreme drought and flood events in unrecorded locations. They follow a general pattern of the significant trend of increasing drought events in the south and flood events in the western and northwestern regions of the Amazon (Callède et al., 2004; Correa et al., 2017; Espinoza Villar, Guyot, et al., 2009; Lopes et al., 2016; Molina-Carpio et al., 2017). RS data other than discharge and water levels can also be used through DA and could be applied in the Amazon, e.g., soil moisture (Baguis & Roulin, 2017; Crowley et al., 2008; Massari et al., 2015); terrestrial water storage change (Khaki et al., 2018, 2019) and flooded water extent. Additionally, the forthcoming SWOT mission will provide breakthrough information for the hydraulic modeling of the Amazon rivers. Many studies have been discussing the utility of the mission to better estimate hydraulic variables in the Amazon, from reach (lower Madeira River; Brêda et al., 2019) to the basin scale (Emery et al., 2020; Wongchuig et al., 2020). New frameworks for the incorporation of satellite altimetry water levels will set up the development of the next generation of hydraulic models for the Amazon, aiming at better representing local processes as water surface heterogeneities that occur due to hydraulic controls as channel width reductions (Garambois et al., 2017; Montazem et al., 2019; Pujol et al., 2020).

Most model applications in Amazon wetlands focused either on parts of the central Amazon floodplains or the whole Amazon basin. The simulation of river floodplains still has some limitations to be accurately performed over complex, dynamic river systems as in the Andes foothills, which are associated with multiple alluvial fans, wetlands disconnected from the main river in terms of surface waters but connected through groundwater (e.g., the groundwater-fed backswamp forests; Hamilton et al., 2007), and relatively quick hydrographs, which in turn hamper RS-based monitoring of variables as inundation extent and water levels. More advances on the estimation of topography along forested wetlands and adjacent channels are necessary, as well as coupled surface-groundwater model techniques. In addition to river floodplains, other types of wetlands exist in the Amazon basin, which is often named interfluvial wetlands (Junk et al., 2011). They combine endogenous and exogenous flooding processes to different degrees (Bourrel et al., 2009), and are more subject to local rainfall and less connected to adjacent rivers (Reis et al., 2019). They are associated with varying vegetation and ecosystem types (e.g., savanna, forest, grasslands). While 1D hydraulic models have proven satisfactory to simulate flooding along river floodplains (Trigg et al., 2009), interfluvial wetlands require a 2D simulation to properly capture the wetland diffuse flow. Fleischmann et al. (2020) provided a first model assessment focusing on the Negro interfluvial wetlands, which are associated with neotectonic events and savanna environment within the Amazon rainforest (Rossetti et al., 2017), and thus largely differ from the central Amazon in terms of flooding, vegetation and soil characteristics. Belger et al. (2011) used a time series of Radarsat images and in situ measurements of water level and local rainfall to estimate changes in inundation in an interfluvial wetland in the Negro basin. 1D models were shown to be unrealistic for simulating surface water elevation in these areas. Future studies should further address the hydrology of these complex wetland systems, including the Llanos de Moxos (Hamilton et al., 2004; Ovando et al., 2018), Roraima (Hamilton et al., 2002), and Peruvian (Kvist & Nebel, 2001) interfluvial wetlands, aiming at better understanding the hydrological differences between floodplains and interfluvial wetlands, which in turn will improve our understanding of the various particular Amazon ecosystems relying on them, and the differences in terms of river-wetland connectivity.

The downstream part of the Amazon basin remains relatively unexplored in terms of hydraulic modeling and RS. This can be explained by the intricate dynamics of the estuary, which has energetic behavior over a broad range of timescales from the intra-daily tides propagating upstream from the Atlantic Ocean through the Amazon delta to the seasonal-to-interannual timescales driven by the hydrology of the basin. Moreover, tidal effects remain sensible up to about 900 km upstream of the river mouth (Kosuth et al., 2009). One of the challenges in the hydraulic continuum of the lower Amazon is the understanding of the relative roles of the upstream forcing and of the oceanic influence in shaping the spatial and temporal patterns of variability of water level, flow velocity, and flooding extent along the course of the estuary. Promising initiatives have been made to model this complex estuary, mostly relying on coastal ocean circulation models, either in two-dimensional configurations (Gabioux et al., 2005; Gallo & Vinzon, 2005), or more recently through full-blown tri-dimensional modeling (Molinas et al., 2020). These studies in particular shed light on the distinct behavior of the tidal waves during their upstream propagation in the Amazon estuary. However, to date, a comprehensive, high-resolution hydraulic modeling framework embracing the complex geometry of the whole hydraulic continuum of the lower Amazon, and accounting for the full range of interactions between oceanic and riverine forcing factors, is lacking. This can be explained, at least partly, by the fact that the monitoring of water level variability is instrumental in the success of hydraulic modeling of the lower Amazon for calibration/validation purposes; however, spaceborne altimetry has been hardly used in the Amazon estuary.

Finally, new EO data as SWOT-derived water levels (Biancamaria et al., 2016), channel water widths (Allen & Pavelsky, 2018; Yamazaki et al., 2014), floodplain topography (Fassoni-Andrade, Paiva, Rudorff, et al., 2020), and soil moisture estimates (SMOS, SMAP), as well as new precipitation data sets (e.g., rainfall estimation using soil moisture data as the SM2RAIN Brocca et al., 2013, 2014), gravimetry missions (GRACE-FO), and techniques to retrieve groundwater storages (e.g., Frappart et al., 2019), open great opportunities for the next decade of hydrological and hydraulic modeling development in the Amazon basin. A major goal of the Amazon modeling community should be to move toward hyperresolution models, capable of providing locally relevant estimates everywhere (Bierkens et al., 2015; Fleischmann et al., 2019; Wood et al., 2011), as well as better representing all processes within the water cycle, including groundwater dynamics which has been misrepresented in most surface water-oriented hydrological models (Miguez-Macho & Fan, 2012; Sutanudjaja et al., 2018). The move to hyper-resolution models has been promoted at a global scale due to the development of new numerical techniques, equation sets, and software engineering, as well as increased computing power (Bates et al., 2018). Such modeling systems could then be coupled to models of other processes, as recently done by researchers aiming at understanding flooding impacts on photosynthesis and biosphere in general (Aderson de Castro et al., 2018), feedbacks between surface waters and atmosphere

(Santos et al., 2019), sediment exports and floodplain trapping (Fagundes et al., 2021; Rudorff et al., 2018), carbon storage and emissions through wetlands and uplands (Hastie et al., 2019; Lauerwald et al., 2020), and dynamics of biogeochemistry cycles at the basin scale or over wetlands (Guilhen et al., 2020). All these efforts will require additional RS data and will move forward our predictability of the effects of ongoing environmental changes in the Amazon basin.

6.3. Aquatic Ecosystems

Floodplains are the largest aquatic system in the Amazon basin, support a diverse biota, and are important to the biogeochemistry and economy (Hess et al., 2015; Junk, 1997; Junk et al., 2011; Melack et al., 2009). Amazon floodplains contain thousands of lakes, thousands of km^2 of vegetated wetlands and are characterized by large seasonal and inter-annual variations in depth and extent of inundation. Hydrological conditions are central to the ecological structure and function of these aquatic ecosystems, and floodplain hydrology is complex because it combines local inputs and regional-scale fluxes with large spatial variability. Applications of innovations in RS and hydrological measurements and modeling to the investigation of Amazon floodplains have led to advances in the understanding of the ecology of floodplains, in general.

Key aspects of hydrology relevant to floodplain ecosystems in the Amazon and elsewhere are the amplitude, duration, frequency, and predictability of variations in discharge and inundation (Melack & Coe, 2021). Two conceptual frameworks of general relevance to river systems were motivated by studies in the Amazon. Junk et al. (1989) emphasized the flood pulse and defined floodplains in terms of river stage, associated physical and chemical conditions, and adaptions of organisms to these conditions; Junk (1997) elaborated these concepts for the central Amazon. Mertes (1997) examined hydrologic aspects of inundation of floodplain systems with RS and simple models and introduced the concept of the perirheic zone, the mixing zone of water from the river and local catchment. Both these conceptual developments are supported by hydrological measurements of Amazon floodplain lakes, the first by Lesack and Melack (1995), subsequently modeled by Ji et al. (2019) and Bonnet et al. (2008, 2017). Floodplains play an important role in the carbon balance and nitrogen biogeochemistry of the Amazon basin and are sites of large fluxes of methane and carbon dioxide to the troposphere and high rates of aquatic plant production. Studies designed to estimate the magnitude and variability of gas fluxes and productivity in the Amazon have combined RS with field data in innovative ways applicable to aquatic ecosystems in general. Melack et al. (2004) used habitat-specific methane fluxes in combination with seasonal changes in the surface water extent of the aquatic habitats derived from active and passive microwave RS to estimate regional methane fluxes. On the mainstem Solimões-Amazonas rivers and their fringing floodplains, annual methane emissions were estimated to vary between approximately 0.7 and 2.4 TgC $year^{-1}$ (Melack et al., 2004). Furthermore, methane fluxes per m^2 were higher during lower water levels than during high water in an Amazon floodplain lake, and fluxes in proximity to vegetation were higher than those from habitats in open water (Barbosa et al., 2020). Richey et al. (2002) and Melack (2016) also used estimates of surface water extent to calculate carbon dioxide fluxes. Guilhen et al. (2020) estimated N_2O emissions from denitrification in Amazonian wetlands by adapting a simple denitrification model forced by open water surface extent from the Soil Moisture and Ocean Salinity (SMOS) satellite and reported a pattern in denitrification linked to inundation.

Seminal approaches with RS data were used to delineate inundated area and extent of flooded forests, open water, and herbaceous plants (e.g., Hamilton et al., 2002; Hess et al., 1995, 2003, 2015; Section 4.2) and used to improve estimates of seasonal and interannual variations in methane fluxes. As described in Section 4.2, new satellite-borne sensors and remote-sensing products can now be used to update such approaches (e.g., Parrens et al., 2019; Prigent et al., 2020). These data can be combined with remotely sensed changes in aquatic habitats, recent field measurements (e.g., Amaral et al., 2020; Barbosa et al., 2020), and modeling (e.g., Potter et al., 2014) to significantly improve estimates of emissions. More generally, the vegetative-hydrologic classification scheme used in these analyses meets the criteria for a "functional parameterization" of wetlands (Sahagian & Melack, 1998), with classes suitable for biogeochemical and biodiversity applications

The primary productivity of aquatic plants is often high but challenging to measure, especially for herbaceous plants with large seasonal and spatial variations. On Amazon floodplains, the productivity of her-

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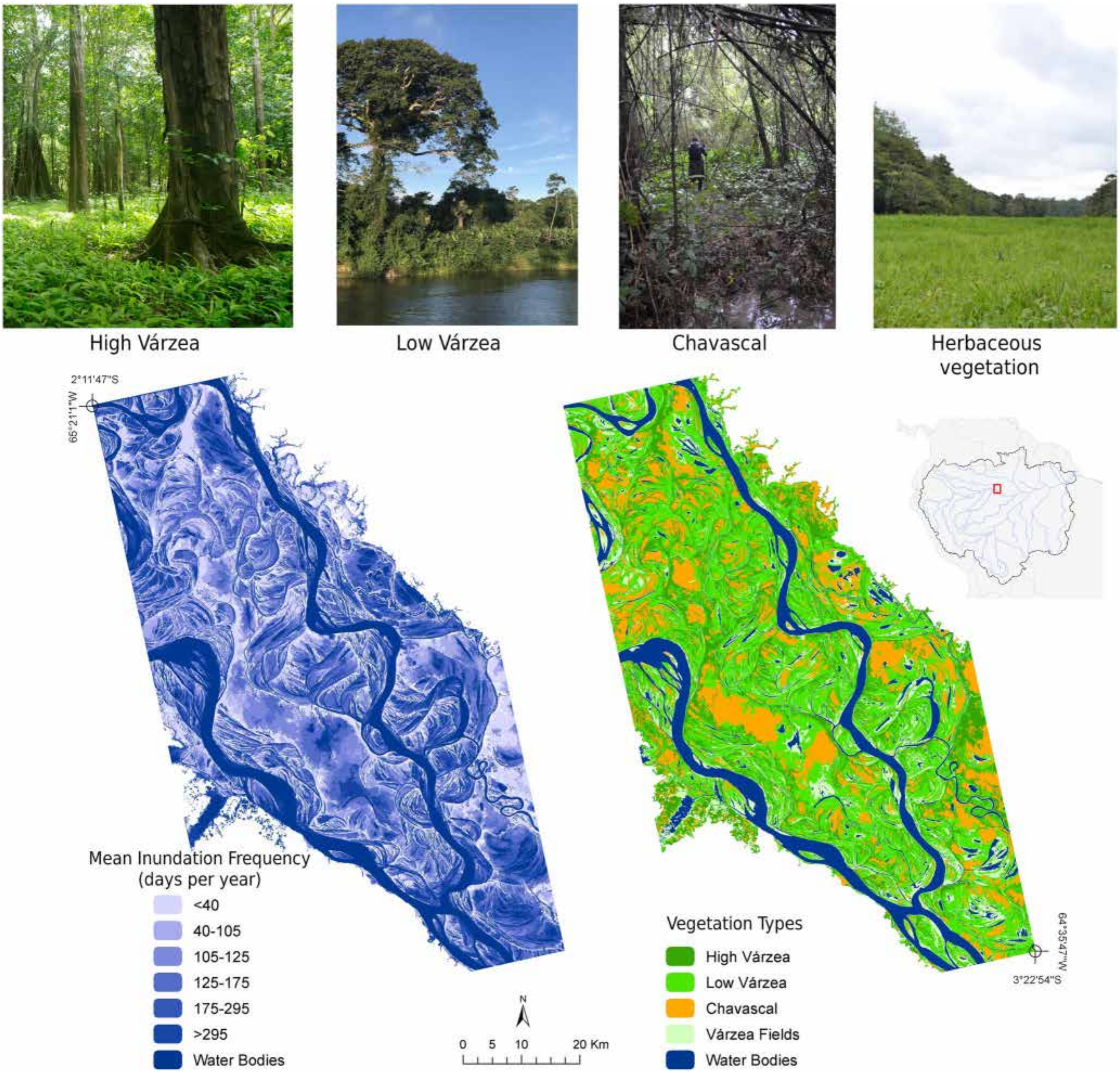

Figure 12. Major vegetation types and estimated mean flood duration maps in the Mamirauá Sustainable Development Reserve, Central Amazon, Brazil (adapted from Ferreira-Ferreira et al., 2015). The maps were based on a time series of ALOS/PALSAR-1 image data comprising nine dates between 2007 and 2010 chosen to provide the largest and most uniform range of water level conditions within the available imagery for the area. The water bodies were derived from the flood class of 365 days per year on average, that is, permanent water bodies. More details on Ferreira-Ferreira et al. (2015).

baceous aquatic plants is strongly influenced by hydrological variations (Engle et al., 2008; Junk, 1997). For instance, the growth of herbaceous aquatic plants in floodplain lakes follows water level variation. Extending field measurements of plant productivity to a regional scale was first done by Costa (2005) using SAR estimates of plant biomass. Lower values were found in regions where plants developed only in the beginning of the flood season, and higher values in areas closer to the Amazon River, where the availability and influence of nutrient-rich water is greater. Further work by Silva et al. (2010, 2013) used C-band SAR combined and optical data to investigate responses of horizontal expansion and vertical growth of herbaceous plants to variations in the flooded area and water level in two large floodplains along the Amazon

River. Over the period from 1970 to 2011 vertical growth varied by a factor of 2 and maximum annual cover varied by a factor 1.5. Years with exceptionally large changes in water level resulted in the highest productivity because horizontal expansion and vertical growth were both enhanced.

The productivity of Amazon aquatic ecosystems is also related to nutrient supply and optical conditions within the water (Melack & Forsberg, 2001). Applications of satellite-borne imaging spectrometers to the optically complex waters of the Amazon have revealed chlorophyll and suspended sediment levels (e.g., Barbosa et al., 2009; Novo et al., 2006; Section 4.4), which are related to planktonic productivity. Other studies employing data from optical sensors have been used to describe aquatic vegetation (e.g., Josse et al., 2007; Novo & Shimabukuro, 1997; Wittmann et al., 2002), and indicate fluvial dynamics (Constantine et al., 2014; Mertes et al., 1995), both important aspects of aquatic ecosystems. However, observations with optical RS are frequently impeded by cloud cover or smoke, and forest canopies are often too dense to allow detection of flooding. Alternatively, time series of SAR data are available for several subregions within the Amazon basin and can be used to generate high-resolution maps of vegetation and inundation. For example, Ferreira-Ferreira et al. (2015) used a hydrologically-based time series of ALOS/PALSAR-1 SAR data to distinguish between land cover classes and map water extent and mean flood duration (Figure 12). The authors depicted the uneven distribution of flooded areas at different water levels, that is, some water level stages result in large expansions of the inundated areas while other stages have less effect.

Complex flow patterns, revealed by interferometric SAR analyses (Alsdorf et al., 2007), and differences in sources of water, evident in hydrological models (Bonnet et al., 2017; Ji et al., 2019), account, in part, for the variations in nutrients, suspended sediments, and productivity (Forsberg et al., 2017). A further example of how advances in hydrological modeling contributed to the understanding of Amazon floodplains is provided by Rudorff et al. (2014a, 2014b). They added a simple model of hydrological balance to the LISFLOOD-FP hydraulic flooding model and applied it over 15 years. This work also emphasized the importance of detailed topography which they derived from a combination of data from the SRTM with extensive echo-sounding. The model simulated well changes in water level, flooding extent, and river-floodplain flows. Rudorff et al. (2018) combined these results with measurements of suspended sediments to demonstrate variations in sediments supply and loss from the floodplain.

Variations in the distribution and inundation of floodplain habitats play a key role in the ecology and production of many commercially important fish in Amazonia. Lobón-Cerviá et al. (2015) demonstrated that number of fish species and their abundance were directly related to the presence of flooded forests and inversely related to distance from the river. Arantes et al. (2018) used both Landsat and SAR data to characterize aquatic habitats and found that spatial patterns of fish biodiversity on Amazon floodplains were associated with forest cover and landscape gradients. Additional examples of connections between fisheries and fish ecology are provided in Melack et al. (2009) and Melack et al. (2021).

Tree phenology on both fertile, eutrophic floodplains (várzea) and nutrient-poor, oligotrophic floodplains (igapó) follow variations in inundation (Junk et al., 2010). Seasonal inundation also provides connectivity that is critical for gamma diversity (Thomaz et al., 2007; Ward et al., 2002). Avian diversity varies among the aquatic habitats (Cintra, 2015; Laranjeiras et al., 2021). At the community level on large river floodplains, birds and fishes have more stable communities in environments with rhythmic annual floods (Jardine et al., 2015; Luz-Agostinho et al., 2009). In a floodplain lake near the confluence of Amazon and Negro rivers, for instance, Röpke et al. (2017) detected an abrupt and persistent change in fish assemblage structure that lasted for more than a decade after the extreme drought of 2005.

Disturbances of the natural variations of the flooded area, hydrological connectivity, or land cover are disruptive for wetland systems. Resende et al. (2019) used SAR RS to assess the impacts of the Balbina dam on the downstream igapó forests in the Uatumã River. The authors showed that 12% of the floodplain forests died because of the altered flood pulse and another 29% of the remaining living forest stands may be undergoing mortality. Schöngart et al. (2021) provide further evidence for changes in floodplain forests below the Balbina dam over 35 years Castello et al. (2018) combined fisheries data and habitat coverage derived from SAR analyses to determine the effects of land cover change on fishery yields. They showed that the removal of flooded forests can reduce fish yields and that other floodplain habitat cannot replace forest removal to improve fish yields.

Several challenges and knowledge gaps remain in the linkage of hydrology to the functioning of aquatic ecosystems in the Amazon basin and elsewhere. Wet soil without standing can have high rates of biogeochemical processes such as methane release. While difficult to detect with RS, models offer promise if operating at the correct scales. Streams and small rivers, as well as ponds, can release disproportionally high amounts of carbon dioxide, but their surface areas are seldom known; high spatial resolution RS products will help alleviate this problem. Interfluvial and savanna wetlands, often inundated by rain rather than rivers, are not well represented by basin-scale hydrological models and will require fine-scale topographic data combined with multi-temporal RS of inundation. Within the Amazon basin, particularly large data gaps exist in the Llanos de Moxos (Bolivia), peatlands in the Pastaza-Marañón foreland basin (Peru), and coastal freshwater wetlands.

6.4. Environmental Changes

In the last decades, Amazon has been subject to large environmental changes. Extensive rainforest areas have been deforested, being converted to pasturelands, croplands, or mining. These land cover changes alter the partitioning of precipitation into evapotranspiration, surface runoff and deep drainage, transport of sediments, river discharge, and river color, and influence the processes of formation of rainfall in Amazonia. At the same time, forest areas have been flooded by artificial dams to produce hydropower, affecting flood pulses downstream of the dam, while the forests' ecohydrology has adapted to the flood patterns. RS has been an important tool to detect and map these environmental changes and their impacts on the hydrological cycle.

The role of deforestation on the Amazon hydrological cycle could only be understood after large-scale mapping of land use and land cover (LULC) in Amazonia. The first of these maps were produced by Cardille et al. (2002). They merged RS imagery from AVHRR with agricultural census data to produce a spatially explicit LULC map for the Amazon and Tocantins basins for 1995. Based on this data set and agricultural census data for 1960, Costa et al. (2003) evaluated how land use increases in the upper Tocantins basin affected its discharge from 1949–1969 to 1979–1999. Although precipitation did not change significantly from the former to the latter period, the annual mean discharge increased by 24% ($P < 0.02$), while the rainy season discharge increased by 28% ($P < 0.01$), and seasonal peaks occurred about one month earlier. Such variations could be credited both to reduced ET and reduced infiltration during the rainy season. The reduction in evapotranspiration is a consequence of three factors: the increased albedo reduces the net radiation at the surface; the reduced roughness length decreases atmospheric turbulence, weakening vertical motions; and the reduced root depth leaves less soil moisture available to plants. Additional factors that can also influence local evapotranspiration include compaction of the soil surface or sub-surface and reduction of leaf area index through grazing (Costa, 2005).

Other LULC maps were produced for the Brazilian Amazon using similar techniques (Leite et al., 2011 for 1940–1995; Dias et al., 2016 for 1940–2012, Figures 13a and 13b). Purely RS products are available for more recent periods, like the MODIS MOD44 tree cover product (2002-recent), Landsat-based PRODES (1988-recent, http://www.obt.inpe.br/prodes/) and TerraClass (2004–2014, https://www.terraclass.gov.br/) official government products for the Brazilian Amazon, and MapBiomas for the Pan-Amazonia (1985-recent, https://mapbiomas.org/ —Figures 13c and 13d). Several authors have used these data sets to study the effects of LULC changes on the hydrological regime of several of the Amazon tributaries and the Amazon-Cerrado arc-of-deforestation as a whole (Arias et al., 2018; Cavalcante et al., 2019; Coe et al., 2011; Levy et al., 2018; Panday et al., 2015; Silvério et al., 2015; Spera et al., 2016), generally finding increased mean and low-flow discharge and decreased basin-wide evapotranspiration with deforestation.

In addition to river discharge, LULC changes may also affect the precipitation, particularly during the beginning and end of the rainy season. The first evidence of this was provided by Butt et al. (2011). They compared four Landsat-based land cover maps from 1975 to 2005 against the rainy season onset dates calculated from daily rain gauge data, concluding that, for stations that lie inside the major deforested area, the rainy season's onset has significantly shifted to, on average, 11 days (and up to 18 days) later in the year over the last three decades. However, for stations that lie in areas that have not been heavily deforested, the onset has not shifted significantly. Recent studies confirmed these results. Repeating the same analysis for southern Amazonia from 1974 to 2012, and after removing regional trends and interannual variability, Leite-Filho

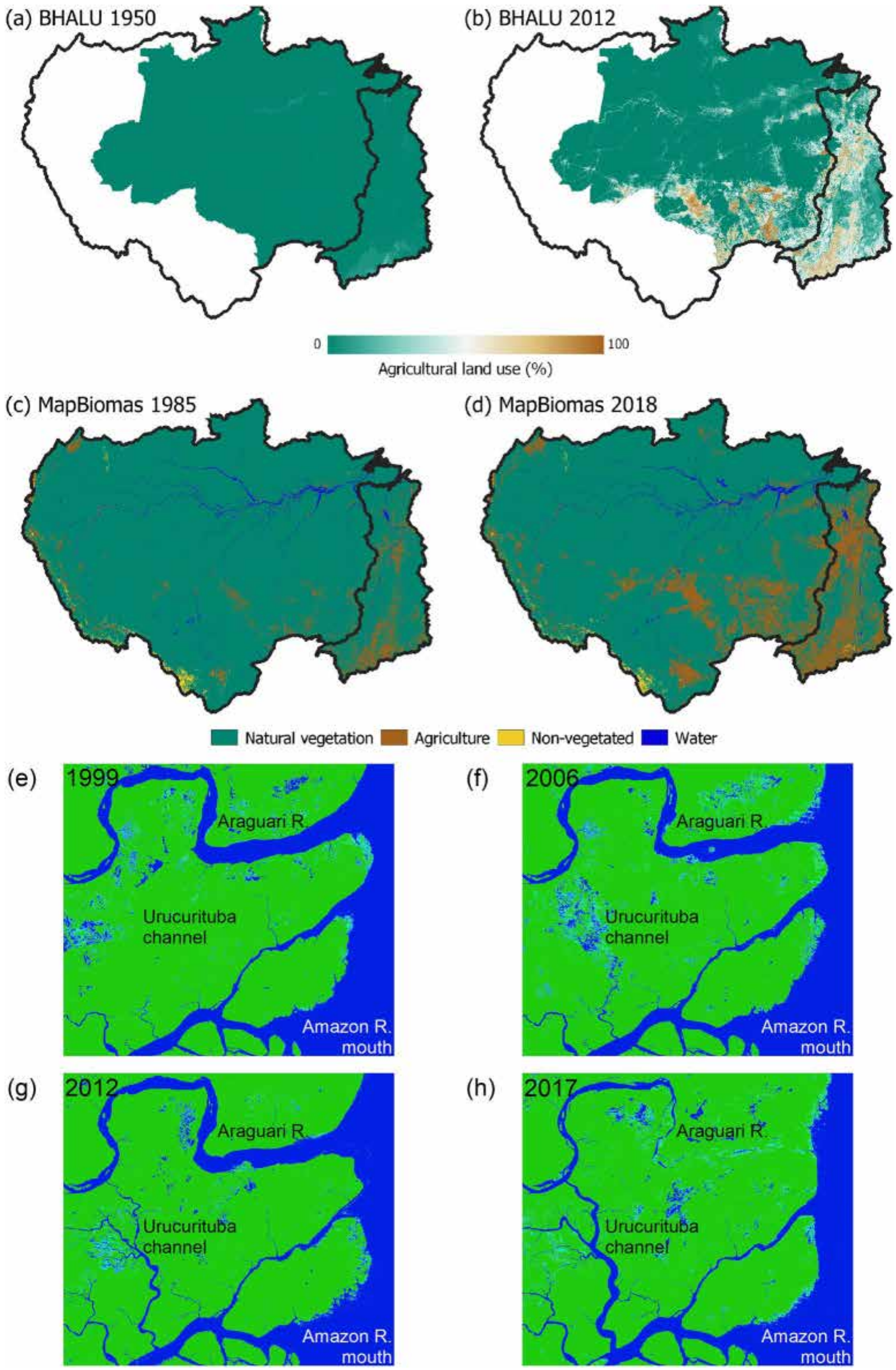

Figure 13.

et al. (2019) confirmed a delay in the onset of 1.2–1.7 days per each 10% increase in deforestation. In addition, the probability of occurrence of dry spells in the early and late rainy seasons is higher in areas with greater deforestation.

Moreover, using daily rainfall data from the Tropical Rainfall Measurement Mission 3B42 product and the Dias et al. (2016) 1-km land-use data set, Leite-Filho et al. (2020) evaluated the quantitative effects of deforestation on the onset, demise, and length of the rainy season in southern Amazon for 1998–2012. After removing the effects of geographical position and year, they verified a relationship between onset, demise, and length of the rainy season and deforestation. Onset delays ~0.4 ± 0.12 days, demise advances ~1.0 ± 0.22 days, and length decreases ~0.9 ± 0.34 days per each 10% deforestation increase relative to the existing forested area ($p < 10^{-5}$ in all three trends).

Another breakthrough owned to RS was identifying the "deforestation breeze" effect, which affects rainfall distribution. Khanna et al. (2017) used remotely-sensed land-use, precipitation, and cloudiness data combined with a regional climate model, finding that small-scale deforestation patches trigger thermally-driven atmospheric circulation cells in Rondônia. This circulation creates a precipitation anomaly dipole over the deforested area, with enhanced precipitation downwind and suppressed precipitation upwind in the thermal cell's descending branch. The observed dipole in Rondônia is substantial, with the precipitation change in the two regions being ±25% of the deforested area mean.

These regional circulation phenomena make the relationship between deforestation and rainfall totals dependent on the scale of analysis. Combining TRMM 3B42 rainfall and PRODES land use data, Leite-Filho et al., (2021) found that this relationship is nonlinear at smaller scales but always leads to a decrease in southern Amazon total annual rainfall at larger scales. At the mesoscale (a 28-km TRMM grid cell), small deforested fractions (up to a 57% deforestation threshold) lead to a slight increase in rainfall (2.2 mm year^{-1} per percent of the cell deforested, $p < 10^{-5}$). However, for deforested fractions above this threshold, rainfall declines at about twice this rate, 5 mm year^{-1} per additional percent of the cell deforested ($p < 10^{-5}$). Aggregating both deforestation and rainfall to larger grid cells (56-km, 112-km) gradually reduces the nonlinear threshold for increase/decrease rainfall impacts. Upon reaching the sub-synoptic scale (224-km grid cell, or 64 TRMM 3B42 pixels), deforestation consistently leads to a linear reduction in rainfall of 4.1 mm year^{-1} per additional percent of the cell deforested ($p < 10^{-5}$) even for small deforestation fractions.

Although several techniques to infer surface water and channel properties from RS have been developed in recent years (as described in Section 4), relatively few studies apply these techniques to assess how anthropic and natural environmental changes affect these properties in the Amazon basin. Latrubesse et al. (2017) used tree cover data from Hansen et al. (2013), Landsat images, and RS estimates of TSS of Park and Latrubesse (2014) to investigate the current and potential impacts of dams in the basin. They found that the Santo Antônio and Jirau dams caused a 20% reduction in mean surface suspended sediment concentration in the Madeira River, despite unusually high flood discharges in the years analyzed after their start-of-operation. They also used Landsat images to calculate channel migration rates for each sub-basin, finding an average migration rate of 0.02 ± 20% channel widths per year.

Satellite retrieval of TSS has also been used to document trends in the Amazon River's main stem, although there is no apparent consensus on the causes of the observed trends. Such techniques allow for expansion and extrapolation of field data sets, being especially useful in the Amazon since runoff and TSS are poorly correlated at the Amazon River's lowest reaches due to asynchronism of the peak water discharges of the Solimões, Madeira, and Negro rivers (Filizola & Guyot, 2009). Martinez et al. (2009) used 18 TSS sampling campaigns from 1995 to 2003 and MODIS images to obtain a 12-year (1995–2007) continuous series of TSS at the Óbidos station, the last gauge station in the Amazon River before it reaches the Atlantic Ocean. They find a 20% increase in sediment discharge in the period with no discernible trends in water discharge and cite changes in land use and rainfall patterns as likely explanations. Recently, Li et al. (2020) used similar

Figure 13. Examples of environmental changes in the Amazon are documented by remote sensing. Panels (a–d) show two different satellite-based land use data sets for the Amazon and Tocantins-Araguaia basins. On top, the Brazilian Historical Land Use data set (BHALU, Dias et al., 2016), which combines satellite and census data to estimate the fraction of each 1 × 1 km pixel occupied by different land uses from 1950 (a) to 2012 (b) in Brazil. The BHALU data set includes areas of natural vegetation, pastures, and croplands. Only total agricultural land use (pastures + crops) is shown. In the middle, the MapBiomas Amazonia data set (MapBiomas Amazonia Project, 2021; https://mapbiomas.org/), a detailed classification of land-use of the combined Pan-Amazonia rainforest area and the Amazon and Tocantins-Araguaia basins from 1985 (c) to 2018 (d). The data set distinguishes 15 land use classes, which were combined in four here for simplicity. The bottom four panels show a major recent hydro-morphological event in the Amazon, the capture of almost all of the water flow from the Araguari River by the Amazon River. The Araguari River used to flow directly to the Atlantic Ocean (e), (f). Starting with a major flood event in 2011, the Urucurituba channel grew until the Araguari River was connected to the Amazon mouth around 2015 (g), (h). Panels (e–h) were drawn using data from the Global Surface Water Explorer (https://global-surface-water.appspot.com, Pekel et al., 2016). See text for more details.

techniques to obtain an updated (1996–2018) time series of TSS and find that sediment loading increased until 2007 but decreased afterward. They infer that this reversal is due to decreased sediment contribution from the Madeira river after the construction of the Santo Antônio and Jirau dams in the late 2000s, in agreement with Latrubesse et al. (2017).

Montanher et al. (2018) used similar techniques to generate an extended 32-year (1984–2016) time series of suspended sediment transport (SST, the product of TSS by river discharge). They argued that there is a recurrent pattern of SST rising and falling in cycles likely associated with climate fluctuations and that trends such as those observed by Martinez et al. (2009) are a consequence of short time series. However, SST depends on river discharge variability, and Martinez et al. (2009) and Li et al. (2020) found no trends in river discharge in their shorter time series.

Some studies also investigated the impact of mining on suspended solids in sub-basins of the Amazon. Artisanal and small-scale mining, especially gold, is common in some regions, such as the Tapajós River basin. These small mining operations often use low-end techniques such as water jets and dredges that can cause proportionally high land degradation levels and water contamination (Lobo et al., 2018). They are also often illegal and unregistered, making RS an important tool for identifying and mapping these activities. The only publicly available data set (to our knowledge) on mining areas in the Amazon basin is the TerraClass project, which is based on visual interpretation of Landsat images and is available only for a few years between 2004 and 2014. Lobo et al. (2018) combined multiple data sets to develop an automated classification method that can distinguish between industrial and small-scale mining and ore types based on Sentinel-2. They found that in 2017 64% of the total mining area in the several key mining regions in the basin comprised small-scale gold and tin mining.

Lobo et al. (2015) estimated total suspended solids (TSS) in the Tapajós River basin based on Landsat images. They found that increases in TSS are strongly associated with reported increases in mining activity at seasonal and decadal timescales. Lobo et al. (2016) updated the Landsat-based identification of mining areas from the TerraClass project. They described the evolution of mining areas in the same basin, identifying different eras of mining impacts on TSS related to the introduction of different technologies and variations in the gold price. Comparing sub-basins with different kinds of land alteration, they also indicated that mining activities have a much higher effect on TSS than deforestation for agricultural purposes.

Landsat images have also been used to document and understand a major hydro-morphological event in the Amazon: the recent capture of almost all of the water flow from the Araguari River by the Amazon River (dos Santos et al., 2018). The Araguari is a large river, with an average annual discharge >1,000 $m^3 s^{-1}$, which used to flow directly to the Atlantic Ocean until the rapid formation of the Urucurituba channel connecting it to the Amazon River in the early 2010s. The initial headwater migration of the proto-Urucurituba was likely associated with deforestation for buffalo farming around 2007. The first connection to the Araguari was attributed to a high flow event in 2011. The rapid growth of the channel, which increased in width by about 5 m per month until 2015, is likely a consequence of complex hydro-morphodynamic processes related to tidal currents and estuarine deposition that ultimately led to the blockage of the Araguari River mouth. This channel's formation caused large changes in the hydraulic pattern, sediment dynamics, and ecosystems in the Araguari estuary, being the first known observation of estuarine distributary network development by headwater erosion.

RS techniques contributed input, calibration, and validation data to many models that provided important insights on the consequences of environmental changes in the Amazon basin (see Section 6.2). These models can integrate hydrological, hydraulic, climate, and land-use processes and are important tools in many studies investigating the impacts of past and future changes in the environment. One of the main applications of these models is to analyze future scenarios (e.g., climate change, deforestation). Another application is attributing the effects of different processes in the variability of the observed data.

Sorribas et al. (2016) examined climate change projections on discharge and inundation extent in the Amazon basin using the regional hydrological model MGB with 1-dimensional river hydraulic and water storage simulation in floodplains forced by five GCMs IPCC's Fifth Assessment Report CMIP5. The model was validated against a mix of in situ and RS data. Results indicate an increased mean and maximum river discharge

Table 7
Synthesis of Scientific Advances in Understanding the Amazon Hydrology With Remote Sensing

Variable	Seminal developments in RS performed in Amazon	Breakthrough lessons about Amazon/General hydrology learned from RS	Knowledge gaps and new opportunities for the Amazon
Precipitation	1) Spatial distribution of rainfall at regional scale (Espinoza et al., 2009). 2) Rain trend over the last few decades (Pacada et al., 2020).	1) Spatial distribution of "hot-spot" regions (Chavez & Takahashi, 2017; Espinoza et al., 2015). 2) Reduced rainfall over main rivers (Paiva, Collischonn, & Tucci, 2011; Paiva, Buarque, et al., 2011). 3) Rainforest inducted early wet season onset (Wright et al., 2017).	1) Improved algorithms for orographic rains (Dinku et al., 2011; Toté et al., 2015). 2) Strategic network of rain gauges. 3) Low-cost satellite constellation (Peral et al., 2019).
Evapotranspiration	1) Water flux estimates in the tropics at large scales (Fisher et al., 2009). 2) Observational data for model calibration and validation and multi-model assessments (Gonçalves et al., 2013; Rocha et al., 2009)	1) Understanding of environmental drivers and *ET* seasonality basin-wide, with more energy limitation and small seasonality in the wettest parts (central Amazon), and the opposite in southern ones. 2) Decreasing ET due to deforestation and cropland expansion (G. de Oliveira et al., 2019; Silvério et al., 2015; Spera et al., 2016; Zemp et al., 2017)	1) Modeling high spatial resolution (<30 m) ET estimates on long time series (>40 years). 2) Combining surface energy balance models and models less dependent on land cover parameterization. 3) New data fusion techniques using multiple RS sources (multispectral, thermal and microwave) to reduce the cloud cover effects on SEB approaches.
Surface water elevation (SWE)	1) Large scale water level and slope estimates by radar altimetry (Birkett et al., 2002; Guzkowska et al., 1990). 2) Water level changes from interferometry estimates (Alsdorf et al., 2000, 2007). 3) Monitoring of SWE and level-discharge rating curves in ungauged rivers (Paris et al., 2016; Da Silva et al., 2014).	1) Characterization of water level variation in rivers and wetland forests (Alsdorf et al., 2007; Birkett et al., 2002). 2) River-floodplain connectivity (Alsdorf, 2003; Park, 2020). 3) Flood storage in river-wetland systems (Alsdorf, 2003; Frappart et al., 2005).	1) 2D characterization of water levels (SWOT swath data; (Biancamaria et al., 2016). 2) Finer spatio-temporal resolution for water level and slope. 3) New techniques for fusion with local to regional modeling (Paiva, Collischonn, et al., 2013; Yamazaki et al., 2011).
Surface water extent	1) First large scale extent and variability of surface water and inundations in floodplains (Hess et al., 2003; Sippel et al., 1994). 2) Relationship between surface water extent and discharge (Sippel et al., 1998). 3) High resolution floodplains dynamic and discrimination of aquatic vegetation types for large area (Ferreira-Ferreira et al., 2015).	1) Seasonal and interannual inundation patterns in the Amazon basin (Aires et al., 2017; Hamilton et al., 2004; Hess et al., 2015). 2) Contribution of inland water and floodplains variability to the Amazon Carbon cycle and emissions (Melack et al., 2004; Raymond et al., 2013; Richey et al., 2002).	1) Finer spatio-temporal resolution of surface water and floodplain inundation extent variability with SWOT and NISAR. 2) New development of fusion techniques with IA to combine various RS observations (visible, IR, passive and active microwave, GNSS-R). 3) Ensure long-term observations to monitor climate/anthropogenic changes.
Floodplain and river channels topography	1) Adjustment of Digital Elevation Models (Baugh et al., 2013; Yamazaki, Baugh, et al., 2012). 2) Topography estimates in seasonally flooded areas (Fassoni-Andrade, Paiva, Rudorff, et al., 2020).	1) Characterization of floodplain channels and lakes (Fassoni-Andrade, Paiva, Rudorff, et al., 2020; Sippel et al., 1998; Trigg et al., 2012). 2) Assessment of river channel migration (Constantine et al., 2014; dos Santos et al., 2018).	1) Characterization of topography in flooded forests. 2) Long-term estimation to monitor geomorphological changes in floodplain and river channels.

Table 7
Continued

Variable	Seminal developments in RS performed in Amazon	Breakthrough lessons about Amazon/General hydrology learned from RS	Knowledge gaps and new opportunities for the Amazon
Water quality: Sediments, chlorophyll and colored dissolved organic matter	1) Estimates of sediment concentration in rivers (Bayley & Moreira, 1978; Mertes et al., 1993), chlorophyll in floodplain lakes (Novo et al., 2006), and colored dissolved organic material in lakes (M. P. da Silva et al., 2019). 2) Semi-analytical algorithms for water quality estimates (Bernini et al., 2019; de Carvalho et al., 2015; Maciel, Barbosa, et al., 2020).	1) Spatiotemporal dynamics maps of the underwater light field and optically active constituents (Fassoni-Andrade & Paiva, 2019; Maciel, Barbosa, et al., 2020; Martinez et al., 2009; Novo et al., 2006). 2) Extended time-series of suspended sediments in the Amazon Region (Li et al., 2020; Martinez et al., 2009; Montanher et al., 2018).	1) Evaluation of phytoplankton community dynamics using RS as a proxy for biodiversity indicator in Amazon waters. 2) Robust algorithms for CDOM and Chlorophyll-a retrieval in optically complex inland waters.
Total water storage (TWS) and groundwater storage (GWS)	1) Large scale estimates of the TWS using GRACE data (Tapley et al., 2004). 2) Determination of GWS changes using RS products and model outputs (Frappart et al., 2011).	1) Spatial signatures of droughts and floods in TWS (Chen et al., 2009). 2) Spatio-temporal signatures of droughts on surface water storage (Frappart et al., 2012; Papa et al., 2013). 3) Temporal variations of GWS (Frappart et al., 2019).	1) More accurate estimates of surface water storage from SWOT will improve the determination of GWS anomalies. 2) Long-term monitoring of TWS and GWS (GRACE and GRACE-FO).

for large rivers draining the Andes in the northwest contributes to increased mean and maximum discharge and inundation extent over Peruvian wetlands (e.g., Pacaya-Samiria region) and Solimões River in western Amazon. In contrast, decreased river discharges (mostly dry season) are projected for eastern and southern basins and decreased inundation at low water in the central Amazon.

With the renewed interest in the last decades in constructing hydroelectric dams in the Amazon basin (Castello & Macedo, 2016), many modeling studies attempted to quantify the environmental impacts of new and existing dam projects. Forsberg et al. (2017) used several models to evaluate the impacts of six planned dams in the Andean region of the Amazon. Since a sizable portion of sediment production in the basin occurs in this region, these dams are predicted to reduce the basin-wide supply of sediments, phosphorus, and nitrogen by 64%, 51%, and 23%, respectively. Along with changes in nutrient and sediment supply, mercury dynamics and flood pulse attenuation are projected by the authors to cause major impacts on downstream aquatic and floodplain fertility and channel geomorphology. Indeed, Resende et al. (2019) found massive tree mortality in floodplain forests (igapó) downstream of the Balbina reservoir using SAR images, with about 40% of the igapó 49 km downstream of the reservoir either dead or undergoing mortality.

Expected environmental changes in the basin, such as deforestation and climate change, can also significantly impact hydropower production itself, often leading to generation well below the dam's expected capacity. Most recent dam designs follow a run-of-the-river concept, avoiding the large environmental impacts of enormous reservoirs from older designs but making power generation more dependent on river discharge variations (Costa, 2020). Arias et al. (2020) combine a land-use and a hydrological model to assess the direct impacts of climate change and deforestation on hydropower production of existing and planned dams in the Tapajós basin. Although decreasing evapotranspiration from deforestation tends to increase annual mean discharge, reduced water retention increases surface runoff and flash flows during the rainy season and reduces discharge during the dry season. Since turbines are normally working at maximum capacity in the rainy season, this excess flow is wasted, and generation in the dry season is reduced. Arias et al. (2020) find that projected climate change and deforestation combined can delay peak energy generation by a month (worsening the mismatch between peak production and consumption), reduce dry season generation by 4%–7% and increase interannual variability of power production by 50%–69%.

Table 8
Synthesis of Scientific Advances in Multidisciplinary and Integrative Efforts in the Understanding of the Amazon Basin Hydrology and Ecosystems

	Breakthrough lessons about Amazon/General hydrology learned	Knowledge gaps and new opportunities for the Amazon
Water budget	1) Sub-basin scale water cycle analysis (Azarderakhsh et al., 2011). 2) Water budget closure enforcement (Pan et al., 2012). 3) Continuous river discharge estimate based on water cycle closure with satellite estimate.	1) Finer spatio-temporal resolution of the water budget analysis using river map information. 2) Sensitivity of the closure to the water component bias, in particular, ET estimate. 3) Groundwater exchange estimate might be obtained at fine-scale in constraining the water cycle at the surface.
Modeling the Amazon water cycle and its wetlands	1) River-floodplain hydrodynamic interactions at local and large scales (Paiva, Buarque, et al., 2013; Rudorff et al., 2014a; Sorribas et al., 2020; Wilson et al., 2007). 2) Groundwater dynamics across scales and climates, and floodplain-groundwater interaction (Miguez-Macho & Fan, 2012). 3) TWS components (surface, subsurface) at basin scale (Paiva, Buarque, et al., 2013; Pokhrel et al., 2013).	1) Finer spatio-temporal resolution of flood dynamics, considering sedimentation processes, in diverse wetland types (floodplains and interfluvial). 2) Better parameterization of groundwater processes across the Amazon basin. 3) Lack of convergence among water storage partitions (e.g., divergent estimates of surface water fraction).
Aquatic ecosystems	1) Integration of temporal and spatial variations of inundation and associated aquatic habitats into the estimation of carbon dioxide and methane fluxes to the atmosphere (Melack et al., 2004; Richey et al., 2002). 2) Areal estimation of major aquatic habitats in Amazon and seasonal and interannual variations in the areas (Hess et al., 2015; Melack & Hess, 2010). 3) Biomass and growth of aquatic plants on floodplains (Costa, 2005; Silva et al., 2013).	1) Extent of saturated soils under forests and in riparian corridors. 2) Modeling of inundation variations in interfluvial wetlands and savanna wetlands. 3) Areal extent of streams and small rivers, especially in the Andean region. 4) High-resolution topographic data on floodplains.
Environmental changes	1) Effects of changes in land use on the river discharge (Costa et al., 2003). 2) Influence on changes in land use on onset of the rainy season (Butt et al., 2011; Leite-Filho et al., 2019), duration of the rainy season (Leite-Filho et al., 2020), and total rainfall (Leite-Filho et al., 2021).	1) Need to better understand the interactions between local changes in land use and large-scale climate mechanisms on the water cycle of the Amazon basin. 2) Initiate monitoring of forest degradation in its different forms, so that the long-term effects on forest hydrology can be studied. 3) Apply existing techniques to assess changes in water and floodplain properties caused by anthropic changes (land use change, damming, mining).

Deforestation has the indirect effect of reducing precipitation and delaying the onset of the rainy season, which further illustrates the dependency of hydropower generation on forests. Stickler et al. (2013) combine land-use, hydrological, and climate models to assess the direct and indirect effects of deforestation alone on hydropower generation of the Belo Monte energy complex in the Xingu River basin. They find that when considering only the direct effects of deforestation on river flow, a 20%–40% deforestation of the basin would lead to a 4%–12% increase in mean discharge with similar increases in power generation. However, when the climate effects of deforestation of the Amazon region were considered, rainfall inhibition in the basin counterbalanced the direct effects and led to a 6%–36% reduction in discharge. Under the business-as-usual deforestation scenario for 2050 (40% of the Amazon forest removed), they simulated that power generation was reduced to 25% of maximum plant output.

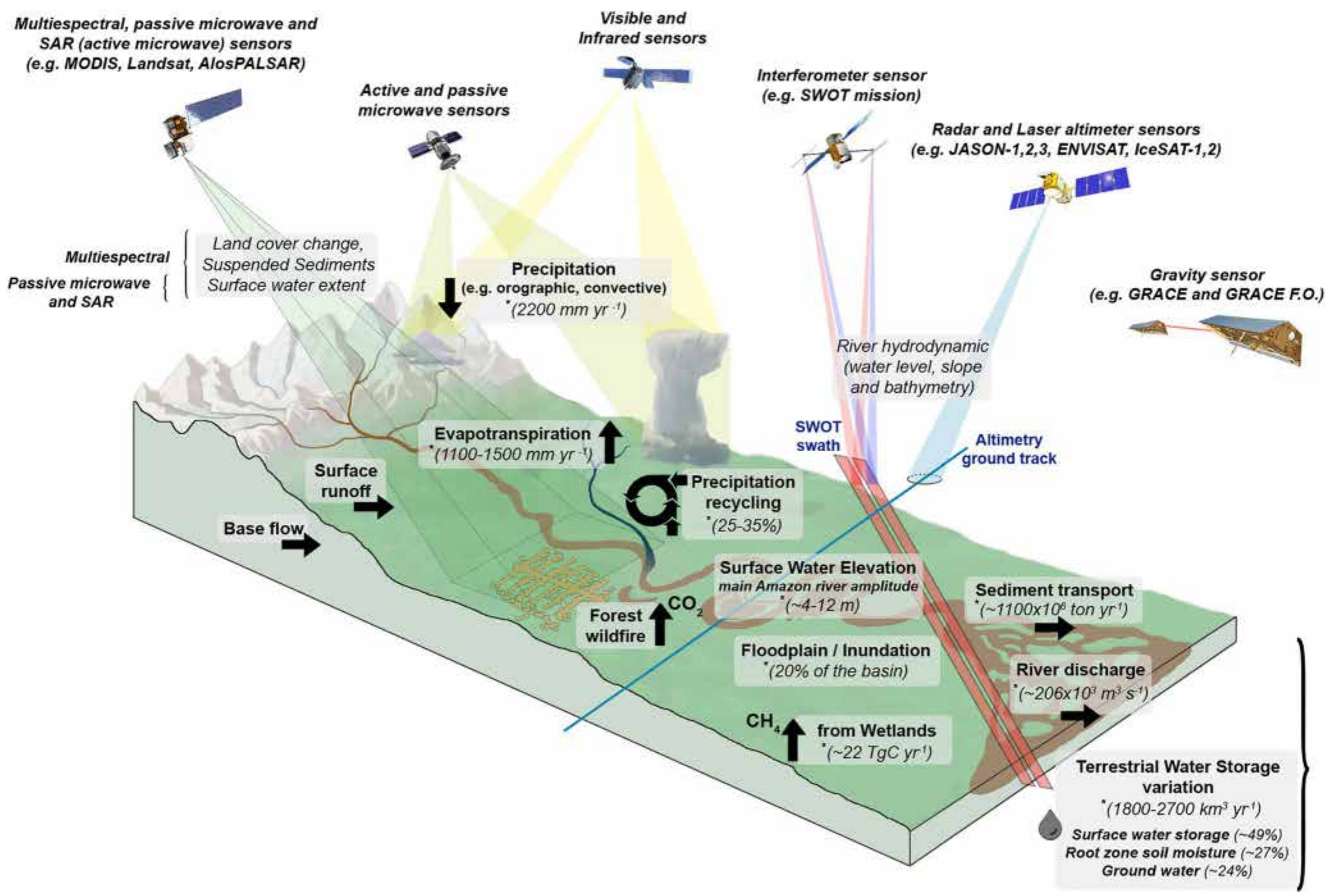

Figure 14. Schematic illustration of the integrated hydrological processes of the water cycle in the Amazon basin. The main sensors on board orbiting satellites that have helped measure these processes are indicated. The annual estimates of each component averaged over the entire basin are shown. The references (*) related to these estimates are provided along with the text in Section 7.1.

7. Synthesis of Scientific Advances, Future Challenges, and Priorities

The various achievements of more than three decades of scientific advances on the hydrology of the Amazon basin with satellite data, along with the development of new RS techniques, and some selected research opportunities, are summarized in Table 7 and Table 8. Section 7.1 presents the main findings obtained in the Amazon, which has been a RS natural laboratory for hydrology advancement. Section 7.2 highlights how these experiences can be used to foster the understanding of the water cycle in other large river basins worldwide. Section 7.3 discusses the knowledge gaps and research opportunities on Amazon waters, thanks to an unprecedented and continued monitoring of the Amazon basin with upcoming and future satellite missions. Finally, Section 7.4 discusses how to move forward from scientific advances toward more sustainable water resources and risk management, and Section 7.5 highlights recommendations for future studies on Amazon waters from space.

7.1. The Amazon Basin as a Remote Sensing Laboratory for Hydrology

As the largest river basin in the world, characterized by strong hydrological signals in precipitation, evapotranspiration, water storage change, and discharge, the Amazon basin has been an ideal natural laboratory for the seminal development of RS techniques and their applications to foster our understanding of hydrological processes. Table 7 summarizes for various hydrological variables key seminal developments made in the RS field over basin along with breakthrough lessons learned regarding Amazon hydrological functioning. Additionally, Figure 14 illustrates the major characteristics of Amazon hydrological storages and fluxes as characterized by RS observations and analyses. Over the past decades, the need to understand the ongoing environmental changes in the Amazon basin, that could impact the global water, energy, and carbon cycles, has motivated a series of multidisciplinary and integrative efforts that foster scientific advances in our understanding of Amazon hydrology and ecosystems (Table 8).

Advances in precipitation estimates from RS have allowed the characterization of the spatial and temporal distributions of rainfall at local to regional scales over the Amazon basin and provide records long enough to assess rainfall trends over the last few decades (Tables 2 and 7 for developed precipitation products). The average rainfall in the basin was estimated as 2,200 mm year^{-1} (Figure 3), and the heaviest rainfall occurs in hot-spot regions in the Andes mountain ranges initiated by convection processes altered by the topography, where rainfall can reach values higher than 6,000 mm year^{-1} (Chavez & Takahashi, 2017; Espinoza et al., 2015; Figure 3). Large-scale analysis of RS-derived precipitation revealed the effect of winds over large water bodies that causes reduced rainfall over these areas (Paiva, Buarque, et al., 2011; Paiva, Collischonn, & Tucci, 2011).

RS observations were key to providing the first large-scale evapotranspiration estimates in tropical regions, especially over Amazon. Also, they provided unprecedented observational data for the evaluation, calibration, and validation of models (Table 2). Furthermore, RS allowed the characterization of ET temporal and spatial variability over the Amazon basin (Figure 4) and the understanding of its environmental drivers, revealing contrasting regimes between the more energy-limited ones in the equatorial part of the basin and more water-limited regimes in the southern areas (Maeda et al., 2017). Amazon basin annual average evapotranspiration is estimated as 1,100–1,500 mm year^{-1} (based on SSEBOp, MOD16, PML, and GLEAM global models—Figure 4, and water balance by Builes-Jaramillo and Poveda (2018), with higher rates in the northern portions, as in the Negro River basin, decreasing toward the southern parts (Baker et al., 2021; Maeda et al., 2017). Various RS-based approaches result in significant divergences in estimating evapotranspiration over the basin (Figures 4 and 10). For instance, RS-based ET annual rates at the basin scale were 15%–37% higher than those obtained from water balances (Baker et al., 2021).

The characterization of continental water surfaces, including their elevation and extent, was possible thanks to adaptations of satellite techniques not primarily designed for hydrology or inland water monitoring applications. A striking example is that of altimetry satellite missions, initially designed to observe the ocean, but with promising applications to the large rivers of the Amazon (Guzkowska et al., 1990) and with the potential to derive SWE of rivers and lakes. Since then, various altimetry databases for the global monitoring of lakes and rivers have been developed (Table 3). The SAR differential interferometry technique, originally developed in geophysics, was also tested and applied for the first time in central Amazon floodplains to characterize SWE changes (Alsdorf et al., 2000). Both altimetry and SAR techniques were important to characterize SWE variations in Amazon rivers and their connectivity with the floodplains (Park, 2020). The water surface gradient of the Amazon River varies both spatially and temporally, with values ranging from 1.5 cm km^{-1} (800–1,020 km upstream) to 4.0 cm km^{-1} (2,900–4,000 km upstream; Birkett et al., 2002). The monomodal flood pulse of the main Amazon River is well captured with radar altimetry (~4–12 m amplitude; Figure 5). This pulse controls the SWE variations in the central Amazon floodplains. During the annual flood, the SWE variations in rivers and adjacent floodplains, as seen from SAR or altimetry, are similar (Alsdorf et al., 2007), but connectivity is reduced during the low-water period (Park, 2020) as the flows are controlled by the local topography (Alsdorf et al., 2007) and SWE in both environments is not always equivalent (Alsdorf, 2003).

The first large-scale surface water extent mapping from RS was also carried out for the Amazon basin (Sippel et al., 1994) using passive microwave observations. Using several sensors, many estimates and databases have been developed at different spatial and temporal scales (Table 4). These include innovative high-resolution mapping of wetlands and flooded vegetation using L-band SAR (Hess et al., 2003), which provided the first estimates of flood extent in the entire Amazon wetlands, ranging between 285×10^3 and 635×10^3 km^2 in periods of low (Oct-Dec) and high waters (Apr-Jun), respectively (Hess et al., 2015; Figure 6). Significant differences among various RS-based estimates of surface water extent exist over basin (Figure 6), with in general lower maximum flooded area found by coarse-scale products than SAR-derived maps. Seminal approaches with RS data were used to delineate Amazon large-scale surface water area and extent of flooded forests, open water, and herbaceous plants, revealing their complex seasonal and interannual patterns influenced by local and regional-scale variability (Aires et al., 2017; Hamilton et al., 2004; Hess et al., 2015; Melack & Hess, 2010). While the width of the Amazon River floodplain is similar throughout the central Amazon, the area of flooded forest decreases from upstream to downstream, where both the number and size of open water lakes increases (Hess et al., 2015; Mertes et al., 1996).

In combination with field data, mapping surface water extent in the Amazon basin enabled pioneering regional estimates of methane emissions (Table 7), with an estimate of methane emissions of ∼22 Tg C $year^{-1}$ for the lowland basin (Melack et al., 2004). The spatial configuration of the Amazon floodplain habitats in relation to vegetation types is related to flooding patterns (Figure 14; Ferreira-Ferreira et al., 2015). Herbaceous aquatic plants on central Amazon floodplains have a growth related to water level variation and the flood extent (Costa, 2005; Silva et al., 2013). Furthermore, the increasing effect of dams in the Amazon basin has been assessed through analyses of flood extent dynamics (Li et al., 2020; Souza et al., 2019) and impacts on tree mortality (Resende et al., 2019).

The first morphometric characterization in the Amazon basin using RS data showed that 11% of the floodplain along the Amazon River and lower reaches of major tributaries is covered with lakes (Sippel et al., 1992). In fact, the floodplain topography along the Amazon River is complex, with several channels and lakes connected to the river (Latrubesse, 2012; Mertes et al., 1996). Floodplain channel widths vary largely (10–1,000 m), and channel depths are tied closely to the local amplitude of the Amazon River flood pulse (8–12 m, Trigg et al., 2012; Figure 7). The recent capture of almost all of the water flow from the Araguari River by the Amazon River, the first known observation of estuarine distributary network development by headwater erosion, was also documented with RS techniques (dos Santos et al., 2018). The need for accurate topographic data for hydrological applications was emphasized in several studies in the central Amazon (Baugh et al., 2013; Wilson et al., 2007; Yamazaki, Baugh, et al., 2012), in which key improvements such as vegetation removal were made. Global DEMs still do not accurately represent the floodplain topography, but surface water extent data combined with WSE allowed the first topographic mapping in seasonally flooded areas in the central Amazon with an accuracy of 0.89 m (Fassoni-Andrade, Paiva, Rudorff, et al., 2020). In these areas, 75% of the open-water areas have a depth of less than 2 m (8 m) in the low (high) water period (Fassoni-Andrade, Paiva, Rudorff, et al., 2020).

The Amazon River exports the largest sedimentary supply to the world's ocean (1.1×10^9 tons per year (Armijos et al., 2020; Figure 14). Several seminal studies and algorithm developments using RS to characterize the water composition of rivers and lakes were primarily conducted in Amazon (see Table 5), such as the pioneering estimates of sediment concentration in rivers (Bayley & Moreira, 1978; Mertes et al., 1993), chlorophyll in floodplain lakes (Novo et al., 2006) and colored dissolved organic material (M. P. da Silva et al., 2019). The spatio-temporal pattern of these components is related to SWE variations and mixing processes from different sources. The shallow depths during the low water period and the large area of floodplain lakes favor conditions for sediment resuspension (Bourgoin et al., 2007; Fassoni-Andrade & Paiva, 2019; Figure 8). The chlorophyll mapping in floodplain lakes showed higher pigment concentrations during the low water season (Novo et al., 2006). Increasing trends in sediment concentration in rivers were linked to changes in land use (Martinez et al., 2009; Amazon River) and the impact of mining (Lobo et al., 2015, 2016; Tapajós River). Conversely, the construction of the Santo Antônio and Jirau dams seems to have contributed to a reduction of sediment concentration in the Madeira River (Latrubesse et al., 2017; Li et al., 2020).

Due to large spatial and temporal changes of freshwater stored in surface, soil root zone, and aquifers, the Amazon basin is the ideal laboratory to explore measurements of gravity field variations from the GRACE satellite mission and derive TWS variations, linked to the redistribution of water mass over the continental surfaces (Figure 9). The first GRACE-derived estimates of TWS variations (Tapley et al., 2004) and groundwater storage changes (Frappart et al., 2011) were presented for the Amazon basin. TWS change in the Amazon is estimated as ∼1,800–2,700 km^3 $year^{-1}$ (Figure 14) with different contributions from surface water storage (∼49%), root zone soil moisture (∼27%), and groundwater (∼24%) (Frappart et al., 2019). The residence time of the water stored in the Amazon basin, that is, the average time that the water remains in the basin before leaving by runoff or evapotranspiration was estimated at two months (Tourian et al., 2018). GRACE data helped to monitor periods of extreme droughts (e.g., 2009) and floods (e.g., 2005, 2010; Chen et al., 2009), quantify water deficit during such events (Frappart et al., 2012), understand groundwater dynamics across different scales and climates, and the interaction between floodplains and groundwater (Miguez-Macho & Fan, 2012).

RS has proven to be a great complement to in situ observations that have traditionally been used to calibrate/assimilate and validate hydrologic and hydrodynamic models (Table 6 and Figure 11). In the case of the Amazon basin, the pioneering development or application of models have provided a major understanding of basin-wide river-floodplain systems (Coe et al., 2002; Paiva, Buarque, et al., 2013; Rudorff et al., 2014a; Sorribas et al., 2020; Trigg et al., 2009; Wilson et al., 2007; Yamazaki et al., 2011), the role of groundwater in hydrological buffering and headwater basin dynamics (Cuartas et al., 2012), and partitioning of total water storage (Paiva, Buarque, et al., 2013; Pokhrel et al., 2013). While Wilson et al. (2007) developed one of the first large scale hydraulic models, the large-scale hydrologic-hydrodynamic model of the entire basin by Paiva, Buarque, et al. (2013) allowed the representation of physical processes such as the backwater effects in the main river and the attenuation of the flood wave due to water storage in the floodplains. These large-scale applications set the way for global hydrodynamic model applications are used today to understand flood risk from continental to Earth scale (Bates et al., 2018, 2021). Applications of two-dimensional models in a reach of the Amazon River showed that the floodplain receives large amounts of water from the river, and small increases in peak discharge promote large changes in this flow (Rudorff et al., 2014b). Recently, Sorribas et al. (2020) estimated, using an innovative hydrological tracking model, surface water travel times along the Amazon basin as 45 days (median), with 20% of Amazon River waters flowing through floodplains. Furthermore, with the integration of RS data and shydrological modeling, the assessment of past floods and droughts was possible (Frappart et al., 2012; Wongchuig et al., 2019).

RS techniques were also important for understanding how the hydrological cycle responds to environmental changes. Long-term changes in discharge could be attributed to changes in land cover via changes in evapotranspiration, as first shown for the Tocantins River (Costa et al., 2003). The average annual discharge increased by 24% between 1949–1986 and 1979–1998, associated with increased agricultural land use in the basin (from 30% to 49%). The presence of the forest was established as important for determining precipitation patterns both in and outside the region. The deep roots, low albedo, and high ET rates of the rainforest induce the wet season onset to be several weeks before what it would be without it, in a mechanism dubbed 'shallow convection moisture pump'(Wright et al., 2017). The changes in land-surface fluxes caused by deforestation were found to cause reductions in precipitation totals, delays on the rainy season onset, and longer dry spells during the wet season, with negative consequences for hydropower generation, regional agriculture, and the resilience of the forest itself (Arias et al., 2020; Butt et al., 2011; Costa, 2020; Leite-Filho et al., 2020; Spera et al., 2014; Stickler et al., 2013).

7.2. The Benefits of the Lessons Learned in the Amazon to Understand the Hydrology of Other Large Tropical River Basins

Amazon basin can be seen as a RS laboratory for fostering the understanding of the water cycle and hydrology in general. While these advances have prompted the scientific understanding of Amazon hydrology, they have also set up new developments, techniques, and analyses that contribute to a better understanding of other large basins' hydrological cycles and at the global scale. Without being exhaustive, here we discuss some key studies that benefit from such advances and how they have contributed to hydrological progress in other regions. In particular, as the second-largest river basin in the world, with similar environmental characteristics as the Amazon basin, such as extensive floodplains and dense forests, the Congo River Basin is the new frontier of tropical hydrological research (Alsdorf et al., 2016), gaining more scientific attention in recent years and benefiting from the lessons learned from Amazon hydrology. The "Hydrologic Research in the Congo Basin" conference in Washington, D.C (USA) in 2018 delineated new research opportunities for the basin. This effort to gather African and international communities around a joint objective of a better understanding of the Congo basin response to climate change led to an extensive monograph (Alsdorf et al., 2021) that indicates the usefulness of RS and model methodologies built for the Amazon basin.

The first development of satellite altimetry data sets (Section 4.1) in the Amazon basin was turned into freely available global data sets providing long-term WSE at thousands of virtual stations (Table 3), enabling the characterization of the surface hydrology variability from altimetry in the Congo basin (Paris et al., 2020), Indian inland waters (Ghosh et al., 2017) and the Niger River basin (Normandin et al., 2018). The integration of satellite altimetry and hydrological modeling had seminal advances in the Amazon, including model validation and development of rating curves for near real-time monitoring of discharges from the space (Section 6.2), that was further performed in other tropical basins as the Congo (Kim et al., 2019, 2021; Paris et al., 2020), Tsiribihina in Madagascar (Andriambeloson et al., 2020), Niger (Fleischmann et al., 2018), and Ogooué (Bogning et al., 2020).

Studies based on initial RS developments in the Amazon further performed comparative hydrology approaches, for instance, by studying jointly the floodplain dynamics in the central Amazon, the Congo, and the Brahmaputra wetlands with SAR (H. C. Jung et al., 2010) and GRACE (Lee et al., 2011), highlighting the unique features of each of these river systems. Amazon basin, with its extensive river floodplains, largely contrasts with Congo Cuvette Centrale, mainly dominated by interfluvial wetlands, with less river-wetland interaction (H. C. Jung et al., 2010). Following studies using SAR observations to map flood and wetlands extent and distinguish vegetation types in Amazon (Section 4.2), seasonal flooding dynamics, water level variations, water storage, and vegetation types over the Congo basin were derived from JERS-1 (Rosenqvist & Birkett, 2002), ALOS-PALSAR SAR and Envisat altimetry data (Kim et al., 2017; Lee et al., 2015; Yuan et al., 2015) or GRACE (Yuan et al., 2017)

The development of large-scale, multi-satellite RS techniques to monitor surface water storage variability, with initial techniques and analysis developed and assessed for the Amazon basin (Sections 4.1 and 5) were further applied to the Orinoco River in South America (Frappart et al., 2015), to study droughts in the Ganges-Brahmaputra River (Papa et al., 2015) and to quantify the relative contribution of surface and groundwater variations in the Mekong (Pham-Duc et al., 2019), the Chad (Pham-Duc et al., 2020) and the Congo (Becker et al., 2018; Yuan et al., 2017) basins.

Given the global relevance in terms of climate and ecosystems, the presence of large floodplains and dimensions in accordance with the resolution of coarse-scale models, many advances and developments of land surface and hydrological models were first assessed over the Amazon basin (Section 6.2), and later prompted the development of global-scale models (Bates et al., 2018; Yamazaki et al., 2011). Examples include the introduction of basin-scale inundation schemes that were later introduced to other river basins (Andriambeloson et al., 2020; Paris et al., 2020), at continental scale (Siqueira et al., 2018) and at the global-scale (Alkama et al., 2010; Decharme et al., 2012; Yamazaki et al., 2011). Recent advances in large-scale sediment transport using RS observations and modeling followed a similar path, with pioneering works in Amazon (Section 4.4) being followed by progress for all of South America (Fagundes et al., 2021).

7.3. Tackling the Current Knowledge Gaps With Future Satellite Missions

This review shows the tremendous achievements made during more than three decades of scientific advance on the hydrology and the water cycle of the Amazon basin with the help of RS. It also helped to identify the various knowledge gaps remaining to promote a comprehensive understanding of the Amazon hydrology. Here, we summarize these knowledge gaps (Tables 7 and 8) and present the new research opportunities with future satellite missions.

Regarding RS-based precipitation, current algorithm challenges involve the definition of dynamic thresholds of temperature brightness in IR sensors and processing of MW data to avoid confusing the summit of the Andes snowy peaks with cold clouds (Dinku et al., 2011; Toté et al., 2015). Better algorithms for detecting solid precipitation are necessary for improved understanding of local processes in Amazon basin headwaters in the Andes Mountains (Hurley et al., 2015; Levizzani et al., 2011; Peng et al., 2014). In situ observations are fundamental for the calibration of remote sensors. Therefore a strategic network of traditional stations and ground-based radars in key points of the Amazon must necessarily be part of a future agenda. Finally, new low-cost technologies such as nanosatellites have proven viable while maintaining scientific requirements, which should continue to be encouraged for future missions (Peral et al., 2019).

RS models can reasonably estimate average ET rates in the Amazon basin, but correctly representing ET seasonality is still challenging, and understanding differences among individual ET components as soil evaporation, transpiration, and an interception. More studies are needed to disentangle the controls ET across the basin (water and energy limitation, and vegetation phenology) since multiple drivers operate simultaneously (Maeda et al., 2017). Besides, a major knowledge gap is a difference between ET Amazon uplands and wetlands, and the effect of open water evaporation on the regional climate. Current satellite-based models need to minimize the use of parameterization (or better constrain it), while the accuracy of input data must be improved. A major limitation of SEB models is their requirement of clear sky conditions, which may be improved by the use of microwave data (Holmes et al., 2018) and the combination with other types of ET models as those based on vegetation index models. In situ measurements are fundamental to achieve this goal, yet today there are only eight flux towers with publicly available data in the Amazon basin. For vegetation index-based models (e.g., MOD16, GLEAM), improving the understanding of soil water deficit controls ET across the basin is also necessary, given the high dependence of these products on soil moisture content. Some breakthrough ongoing and future missions will provide a new understanding of ET dynamics in the Amazon basin. The ECOSTRESS is addressing the response of vegetation to water deficit with unprecedented details, while the VIIRS collects visible and infrared imagery, extending the time series from its predecessor MODIS and improving its estimates, and the FLEX mission will map vegetation fluorescence, a proxy of photosynthetic activity and vegetation stress and health. The continuity of the Landsat missions will ensure the development of long-term ET at a high spatial scale, while the GRACE-FO mission will provide new data for water balance approaches to estimate ET. This will ultimately allow us to model ET at high spatial resolution (<30 m) and for long time periods (>40 years).

The surface water bodies and aquatic ecosystems of Amazon are still challenging the current available RS observations. Despite the substantial progress in the last decades, there are still limitations. Currently, there is a trade-off over the Amazon basin between spatial and temporal resolutions in satellite observations, with generally high temporal sampling associated with lower spatial resolution and vice-versa. Therefore, there is a need for a finer spatio-temporal resolution to adequately monitor water extent, level, and slope of the surface water and floodplain inundation. There is also a need to improve the accuracy of these estimates to understand more local phenomena, such as floodplain-river exchanges and dynamics or the complex flooding processes of extensive interfluvial areas. Similarly, only a few lakes and reservoirs in Amazon are monitored routinely from space, using altimetry. With dense vegetation and cloud cover, the context of the Amazon basin makes it still challenging to monitor surface waters such as permanently or seasonally flooded forests and floating herbaceous plants.

The forthcoming NASA/ISRO L-band SAR mission, with its combination of radar wavelengths and polarizations and 12-day orbit passes, will help to precisely measure small changes of surface water extent in the Amazon basin, including areas with standing vegetation. Furthermore, with its technology based on swath altimetry from the KaRIn, quasi-global coverage, and joint observation of surface water elevation, extent, river width, and slope, the SWOT mission, to be launched in 2022, will permit unprecedented monitoring of Amazon surface water and rivers at 100 m resolution in two horizontal dimensions. The centimetric accuracy in SWE and slope (Desai, 2018) will help to better characterize freshwater fluxes in the Amazon basin. The current satellite altimetry missions, especially the Copernicus program, are now setting the era of operational monitoring from space at large-scale for the coming decades, with clear benefits for large tropical transboundary watersheds such as the Amazon basin. With nearly two thousand virtual stations distributed over the basin, potentially hundreds more, freely available on multiple websites, conventional satellite altimetry can favorably complement the traditional and necessary in situ network. Since the main limitation for broader use of current satellite altimetry remains its relatively low temporal sampling, future missions in development, such as SMASH (Blumstein et al., 2019), broadcasted together with the current constellation, should help to tackle this issue. Further developments in satellite observations are nevertheless required to fully characterize Amazon surface water extent and elevation. They should combine, in the future, the benefits of SWOT swath global measurements with a high temporal sampling of SMASH-like constellation into a SWOT-like satellite constellation providing global and daily observations.

Besides the concept of new satellite missions, it is worth noticing that the upcoming unprecedented availability of information regarding Amazon surface water extent and elevations will challenge the current analysis capabilities. New development of analysis tools or fusion techniques with artificial intelligence to combine various RS observations (visible, IR, MW, and GNSS-R) is needed. Similarly, new techniques for fusion with local to regional modeling, data assimilation, and better constraining of uncertain hydraulics should also dramatically increase our capacity to model the Amazon basin and the variations of its water cycle.

Floodplain and river channel topography and bathymetry have not yet been fully characterized in the Amazon basin, despite recent efforts with local and regional estimates, preventing a better understanding of habitats related to flood pulse and limiting the accuracy of hydraulic models. In addition, the association between sediment concentration in rivers and channel migration is still poorly understood (Constantine et al., 2014). The development of new techniques and RS data for topography mapping is needed. The main challenge is vegetation removal, as many bands and sensors cannot penetrate vegetation. LiDAR and altimetric data, such as ICESat-2 (launched in 2018), which allow bare earth mapping, have still been little exploited in the Amazon basin for this task.

Interferometry and altimetry data have been used in the Congo basin to derive the floodplain bare earth DEM (Yuan et al., 2019), despite not being able to provide continuous topography. Furthermore, NISAR and SWOT satellites will open opportunities with more accurate estimates of the surface water extent and distributed SWE over water bodies. Thus, new methodologies for topographic mappings, such as the waterline method (Salameh et al., 2019) and Flood2Topo (Fassoni-Andrade, Paiva, & Fleischmann, 2020), can be further developed. Nevertheless, observing river and floodplains bathymetry from space will remain a continuing challenge since adequate solutions for its direct measurement are still lacking, even if future altimetric observations seem to open a new way forward.

White, black, and clear water rivers of the Amazon basin have particular characteristics with large variations of COA (sediment, chlorophyll, and CDOM). Despite the development of many algorithms for estimating these components, little has been explored to implement those algorithms to address scientific questions, as Topp et al. (2020) reported worldwide. In addition, the characterization of natural processes, such as the spatio-temporal variation of phytoplankton in lakes, has not been widely explored. Sediment concentration estimates could be better exploited to assess the effects of dams, mining, and land use changes in the Amazon basin. On the other hand, there are still technical challenges for these estimates using RS data, such as the high cloud cover in the basin. The main challenge is discretizing the COA spectra, which can be partially overcome with new sensors with high radiometric and spectral resolution.

The recent launch of the GRACE-FO mission offers an opportunity to extend the monitoring of TWS and GWS changes over more than two decades, allowing us to start analyzing the impact of multi-year climatic events such as ENSO on land and groundwater storage throughout the Amazon basin. The major drawbacks of these data remain their low spatial and temporal (~200 km and 1 month) resolutions which are not sufficient to study the dynamics of more local and rapid hydrological events. To overcome these drawbacks, the GRACE-FO payload contains advanced versions of the sensors used on GRACE, allowing a better-expected accuracy to improve the quality and the spatial resolution of the retrieved TWSA. Combined with new methodological approaches based on a Kalman filter, it should increase the TWSA temporal resolution to quasi-daily without degrading the spatial resolution (Ramillien et al., 2015, 2020). With the upcoming availability of SWOT observations, unprecedented and finer estimates of surface water storage over large areas will improve the determination of GWS anomalies. They will allow us to understand better the interactions between flood dynamics and aquifer recharge in the Amazon basin. Groundwater exchange in the basin, which remains poorly characterized with satellites, should also benefit from integrating these new observations and could be further estimated in better constraining the water budget at the surface. A comprehensive set of observations dedicated to hydrology, with the continuity of the current satellite missions, is mandatory to improve our understanding of hydrology patterns through more precise water budget analyses and to assess long-term trends.

Given the uncertainties in both hydrological models and RS estimates, model calibration and data assimilation techniques have been recently developed by incorporating mainly water level (satellite altimetry) data and, to a lesser extent, GRACE TWS. Other variables to be better assimilated are flood extent and storage, soil moisture, and evapotranspiration. While most hydrologic and hydraulic model applications have been used to estimate variables such as evapotranspiration, soil water storage, river discharge, surface water elevation, and extent, new studies must investigate other variables such as water flow velocity and flood storage. There is also a lack of convergence among water storage partitions (e.g., divergent estimates of surface water fraction), which must be addressed by better constraining models with EO observations and by performing model intercomparison projects. On the other hand, while the Amazon wetlands were mainly studied for the central Amazon floodplains, other types of wetlands do exist, as the interfluvial ones in large areas of the Llanos de Moxos, Pacaya-Samiria, and Negro. They deserve more efforts from the hydrological community, especially considering their particular flood dynamics, more dependent on local rainfall.

Furthermore, high-resolution 2D modeling of the full Amazon mainstem mapping velocity fields and the complex river-floodplain interactions still are not explored. The downstream part of the Amazon basin remains relatively unexplored in terms of hydrodynamic modeling and RS, for example, the relative roles of the upstream forcing and the oceanic influence on the dynamics of the river-estuary-ocean continuum. In addition to a better representation of hydrological processes, for example, groundwater dynamics that are poorly represented in surface hydrology-oriented models, hydrologic-hydrodynamic models' future depends on the growing availability of new EO data. These include SWOT-derived water levels and discharges, channel water widths, floodplain topography, soil moisture (e.g., SMOS, SMAP), precipitation (e.g., SM2RAIN), gravimetry (GRACE-FO), and techniques to retrieve groundwater storages (e.g., Frappart et al., 2019). These data will promote the basis for modeling estimates at the high temporal and spatial resolution, aiming ultimately at providing locally relevant hydrological estimates everywhere (Bierkens et al., 2015; Wood et al., 2011).

While most major components of the water cycle have been relatively well addressed in the literature, as shown in this review, soil moisture stands out as the less reliable component. This low reliability relates to the difficulty of retrieving this variable under densely vegetated areas (Prigent et al., 2005). The relatively poor performance of current soil moisture data sets (e.g., SMAP, AMSR-E, and SMOS) in these environments is well known, even when products are combined (Liu et al., 2011) or merged (Aires et al., 2005; Kolassa et al., 2016). Most soil moisture-oriented studies were performed with hydrological models and in situ data in a few headwater locations. Moreover, there is an inherent ambiguity in passive microwave observations between water-saturated soils and surface waters. Consequently, the large surface water fraction in the Amazon basin affects the soil moisture retrievals by this type of observation. This ambiguity in the satellite observations has triggered the development of a product such as a SMOS-based surface water product (Parrens et al., 2017). There is an urgent need to better monitor soil moisture at different spatial-temporal resolutions in the Amazon basin, especially considering its major role in controlling the Amazon forest dynamics and phenology, evapotranspiration, and the water cycle in general. This observation supports the development of SMOS-HR, the High-Resolution follow-on mission of SMOS, which is currently undergoing feasibility study by the French space agency and which goal is to ensure continuity of L-band measurements while increasing the spatial resolution to ∼10 km without degrading the radiometric sensitivity and keeping the revisit time of 3 days unchanged.

Similarly, river discharge, historically one of the first hydrological variables that have been observed in situ, is still not properly measured from space. This review stresses a need to accurately estimate river discharge using RS in Amazon with fine spatial and temporal resolution. River discharge has already been estimated indirectly by RS data (e.g., Brakenridge et al., 2007; LeFavour & Alsdorf, 2005; Tarpanelli et al., 2013; Zakharova et al., 2006), but still poorly complements the current in situ network of the Amazon basin. Upcoming missions, such as SWOT, in combination with current satellite missions, will soon help us move toward more comprehensive monitoring of river discharge in the Amazon basin.

The ongoing and future environmental alterations in the Amazon basin urge the understanding of the basin hydrology under the perspective of a changing system. The long-term effects of multiple human impacts (land use change, climate change, damming, mining, and fires) on the Amazon must be better understood. Changes in land-atmosphere feedback due to deforestation will affect the Amazon water cycle, but the magnitude of this change is still under debate. There is relatively little understanding of how they interact, especially in terms of how the impact of land-use changes in local climate can be different under large scale meteorological conditions that are changing with the global climate (e.g., Leite-Filho et al., 2020) and how these would affect the land and water ecosystems in the basin. Furthermore, techniques to map forest degradation and discern primary and secondary vegetation are still relatively new. The impacts of those subtler but pervasive land-use changes on Amazon hydrology are yet to be understood. Finally, although the influence of the Amazon forest on the hydroclimate outside the Amazon has been increasingly documented, the consequences of its deforestation and degradation outside the basin are yet to be understood.

Furthermore, the proliferation of dams in tropical basins as the Amazon, Congo, and the Mekong require basin-scale planning and analysis tools to foster mutual benefits in understanding these changes (e.g., Biswas et al., 2021; Latrubesse et al., 2017; Schmitt et al., 2019; Winemiller et al., 2016), and RS data stand out as powerful tool to monitor large scale impacts of existing man-made reservoirs (e.g., Resende et al., 2019), and infer their characteristics, such as water level and stage-area-volume relationships (e.g., Fassoni-Andrade, Paiva, & Fleischmann, 2020; Gao et al., 2012; Hoek et al., 2019). Better data and knowledge of these impacts are also the base for better hydro-geomorphological models that could quantify the expected impacts of planned reservoirs and, therefore, aid in creating designs that minimize environmental impacts.

7.4. How to Use RS-Based Scientific Advances to Foster Water Resources Management in the Amazon Basin?

While the Amazon basin served as an important natural laboratory for RS development that produced significant scientific advances related to its hydrological processes in the last decades (Tables 7 and 8), the Amazon is currently undergoing extensive anthropogenic pressure (Section 6.4) and urgently calls for better basin-scale water resources planning and new environmental monitoring tools. RS has the potential to democratize essential information for decision-makers, for instance, to monitor "politically ungauged" regions where information is not publicly available (Gleason & Durand, 2020). Although RS is now a reality and documented knowledge on the Amazon basin is much better than decades ago, there is still an open road to move all these advances toward effective applications in decision making and water resources management.

Deforestation and fire monitoring may be the most advanced and promising examples in the context of Amazon environmental management. Since 1988, satellite-based monitoring systems using MODIS, Landsat and CBERS imagery as the DETER (Diniz et al., 2015, http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/deter/), PRODES (http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes), Imazon (https://imazon.org.br/categorias/boletim-do-desmatamento/) and Queimadas (http://queimadas.dgi.inpe.br/queimadas/portal) have been systematically supporting local governments and NGOs on the monitoring and control of deforestation and fires. Technical advances made it possible to monitor deforestation in near real-time, on the scale of days, weeks, or months. However, institution building and related civil-society engagement are still needed to facilitate effective actions within complex government frameworks and bridge the gap between technology and policy toward deforestation reduction (Finer et al., 2018).

Amazon neighborhood countries have mature Water Resources Agencies, Geology and Hydrometeorological Services as the ANA, the Peruvian and Bolivian National Meteorology and Hydrology Services (SENAMHIs), and the Brazilian Geological Survey (CPRM). These institutions have dedicated efforts to the challenging task of systematically monitoring Amazon's vast territory and rivers and promoting open hydrological data sets. In this sense, RS is starting to be incorporated into operational monitoring (e.g., SIPAM http://hidro.sipam.gov.br/, Hidrosat, Carvalho et al., 2015; near real-time flood simulations at sub-daily scale, Llauca et al., 2021). In particular, precipitation has been widely monitored through RS data by multiple meteorological agencies, while other water cycle variables have received less attention. These organizations have been developing technical reports about the national situation and water resources planning, including the Amazon basin (e.g., Water Resources Situation Report, Agência Nacional de Águas, 2019a; National Water Security Plan, Agência Nacional de Águas, 2019b; flow forecasts at the national level and at hourly and daily scale by SENAMHI Peru available at: https://www.senamhi.gob.pe/?&p=pronostico-caudales). Currently, they are mostly supported by the national hydrometeorological networks that are still scarce and could be greatly enhanced with the data and knowledge produced by RS. Some of these countries also have advanced Water Resources Laws and regulations, such as the Brazilian National Water Resources Management System created by Law 9433, 1997 (Brasil, 1997), but most of the efforts on the development and implementation of such regulation are devoted to river basins in more densely populated regions and not in the context of the complexity of the international/transboundary and larger river basin of the world. Also, even though the Amazon basin is in the epicenter of international scientific discussion, it appears not to be the main focus of technical and scientific developments on the water resources field in the Amazon countries, as revealed by the recent synthesis of advances from Brazilian hydrology community (Paiva, 2020).

Most flooding studies in the Amazon aimed to understand ecosystem services and the natural system (Sections 4.2 and 6.2). Still, many Amazon urban centers are at flood risk (e.g., Amazon River at Iquitos, Madeira River at Porto Velho, Acre River at Rio Branco, Juruá river at Cruzeiro do Sul), and suffer annually from overbanking flow (Fleischmann et al., 2020). While this paper was being drafted, the Brazilian Acre state was recovering from a humanitarian crisis caused by floods at Acre River at Rio Branco, Juruá River at Cruzeiro do Sul, and Negro River at Manaus, enhanced by the COVID-19 pandemic. Thus, the several flood monitoring tools developed could be translated into effective flood risk mapping and real-time monitoring for disaster management. International initiatives such as the Copernicus Emergency Management Service (https://emergency.copernicus.eu/) and the International Charter "Space and Major Disasters" (https://disasterscharter.org/) have the potential to provide important EO data for real-time disaster management. Furthermore, the transboundary character of many Amazon sub-basins (e.g., Madeira River, with floods at Porto Velho in Brazil being partially generated in upstream Bolivian reaches) makes RS data a fundamental tool to fulfill the disparity in data availability among countries. On the other hand, in many areas of the Amazon, droughts have a larger societal impact than floods, given the adaptation of livelihoods to the annual flooding regime and the interruption of the provision of goods and general transport through rivers during extremely dry periods (Zeng et al., 2008). Recent technical efforts include evaluation of hydrological forecasts from physically based hydrological models supported by RS (Section 6.2), development of site-specific statistical forecasting and real-time monitoring systems (e.g., SACE system from http://www.cprm.gov.br/sace/; systems available for the Madeira, Acre, Xingu, Branco and some reaches of the Amazon mainstem), prototypes of hydrological model-based monitoring systems (e.g., South America River Discharge Monitor - SARDIM https://sardim.herokuapp.com/; Reis et al., 2020), global flood forecast systems (e.g., GLOFAS, Alfieri et al., 2013) and efforts on monitoring and alerts of natural hazards by centers as CEMADEN from Brazil (Centro Nacional de Alerta e Monitoramento de Desastres Naturais). Drought monitor systems based on in situ and RS-based observations and local community interpretation (e.g., ANA Drought Monitor http://monitordesecas.ana.gov.br/) are evolving, and there are no operational hydrological forecasting systems at the Amazon basin, national or continental scales (Fan et al., 2016).

Impacts from human activities may propagate through the Amazon River network and neighbor countries since the ongoing developments of hydropower projects, and agricultural expansion alters the hydrological, sediments, and ecosystem dynamics (Anderson de Castro et al., 2018; Forsberg et al., 2017). Recent research has explored integrated planning looking for the best hydropower development solutions (Almeida et al., 2020; Winemiller et al., 2016), while organizations, like the Amazon Cooperation Treaty Organization, aim to promote sustainable development at the Amazon basin with the participation of its neighboring countries. However, current national-scale policies and regulations do not promote fully integrated water resources planning, as new projects are usually accessed individually. RS can encourage a common and transparent understanding of Amazon water-related issues.

The RS scientific community now has the challenge to promote knowledge, data sets, and applications on water-environmental changes, aiming at enhanced water resources management and planning. Potential pathways include: (a) training decision-makers and multiple stakeholders on the language of RS (e.g., Applied Remote Sensing Training Program - ARSET https://appliedsciences.nasa.gov/what-we-do/capacity-building/arset), (b) encouraging local engagement by bridging the gap between RS based science and in situ and traditional knowledge (Runde et al., 2020), (c) initiatives of science communication and citizen science (Buytaert et al., 2014; e.g., www.amazoniacienciaciudadana.org/, https://www.ufrgs.br/conexoesamazonicas/, https://ipam.org.br/biblioteca/?biblioteca=artigos-cientificos, https://imazon.org.br/categorias/outros/, https://infoamazonia.org/), (d) development of open access data sets focused on specific applications (e.g., aquatic ecosystem conservation; Venticinque et al., 2016); (e) developing monitoring systems focused on environmental changes and water-related disasters, (f) developing open hydrological repositories (e.g., HYBAM, https://hybam.obs-mip.fr/, SERVIR-Amazonia, https://servir.ciat.cgiar.org/), and (g) developing a basin-scale research agenda focused on directly supporting water resources decision making (e.g., scenarios of hydropower development; Almeida et al., 2020).

7.5. Recommendations

Based on the knowledge gaps and the perspectives presented in the previous sections, we provide the following recommendations for future studies on Amazon waters from space.

10.1029/2020RG000728

7.5.1. Recommendation 1: Observations

Current limitations of satellite data for the Amazon basin are often related to the space-time resolution (e.g., SWE and slope, surface water extent, ET), time span (e.g., surface water extent, TWS, GWS, ET, topography), and accuracy (e.g., surface water extent, GWS anomalies). The largest limitations in monitoring the Amazon hydrology from space refer to soil moisture and river discharge, which have been poorly addressed due to vegetation interference in sensors or by the nature of the variable, respectively, which hampers its estimation from the space. Similarly, river and floodplain channel bathymetry provides great challenges, that may be solved with the assimilation of altimetry data into models. The increasing availability of long-term archives of RS data sets should be ensured by national space and water agencies in complement to existing in situ monitoring networks, which are fundamental to properly calibrate and validate RS estimates. The latency time of RS data distribution (e.g., precipitation and SWE) should be reduced to a few hours to be used by water/risk management. Ensuring satellite observation to be archived into climatic data sets can foster the understanding of the impacts of climate change and human activities on the basin.

7.5.2. Recommendation 2: Models, Algorithms, and Integration

Technical limitations are related to the development of algorithms (e.g., orographic rains, CDOM and chlorophyll retrieval, water budget closure, and hydrodynamic models), and data fusion (e.g., ET, SWE, and surface water extent). The recognition of uncertainties in multiple RS data and trade-offs between temporal and spatial resolution point to the need for more integrative approaches, for example, for mapping long-term flooding and evapotranspiration patterns at high spatio-temporal resolutions, and artificial intelligence will play a major role in this. The better coupling of EO data sets with hydrological-hydraulic models and land surface models (e.g., data assimilation, spatiotemporal interpolation) is also a necessary step forward in Earth System modeling by considering the dynamic aspect of Amazon hydrology.

7.5.3. Recommendation 3: Characterization of Hydrological Processes in a Changing Amazon

The development of long-term data sets is fundamental to understand Amazon hydrological processes across multiple decades. While RS data currently focus on a set of a few hydrological variables, many others require more attention from the hydrologic community, such as river discharge and water velocity, surface and groundwater storage, soil moisture, CDOM, and Chlorophyll-a. Most studies in the Amazon basin also focus on a few areas (e.g., the várzea environment in the central Amazon floodplains), and many other complex river-wetland systems or streams and small rivers, especially in the Andean region, also require attention. Upcoming and future satellite observations will bring new opportunities for the Amazon basin regarding the characterization of natural processes, including phytoplankton in waters, floodplain topography, aquatic ecosystems, groundwater dynamics, and the monitoring of anthropogenic environmental changes.

7.5.4. Recommendation 4: Toward the Use of RS to Support Sustainable Science in the Amazon Basin

The Amazon basin harbors an incredibly large and still poorly known biodiversity, which provides massive ecosystem services for the globe and some of the most complex and intriguing river-wetland systems in the world. While EO through satellites has provided breakthrough scientific advances on the comprehension of the Amazon water cycle in the last decades, the forthcoming years with the new hydrology-oriented missions will provide a new milestone on monitoring Amazon waters from space. Advance knowledge from RS should be translated into valuable information and indicators to support the Amazon basin's environmental governance and sustainable science. RS has the potential to democratize essential information for decision-makers, moving toward a more sustainable future for the largest basin in the world.

Data Availability Statement

This is a review study for which no new data was generated. Data supporting the figures are available via the cited references.

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