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# ▶ To cite this version:

Ayan Santos Fleischmann, Fabrice Papa, Alice César Fassoni-Andrade, John Melack, Sly Wongchuig, et al.. How much inundation occurs in the Amazon River basin?. Remote Sensing of Environment, 2022, 278, pp.113099. 10.1016/j.rse.2022.113099 . hal-03701905

# HAL Id: hal-03701905 https://hal.inrae.fr/hal-03701905

Submitted on 19 Mar 2024  $\,$ 

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Accepted refereed manuscript of: Fleischmann AS, Papa F, Fassoni-Andrade A, Melack JM, Wongchuig S, Paiva RCD, Hamilton SK, Fluet-Chouinard E, Barbedo R, Aires F, Al Bitar A, Bonnet M, Coe M, Ferreira-Ferreira J & Silva TSF (2022) How much inundation occurs in the Amazon River basin?. *Remote Sensing of Environment*, 278, Art. No.: 113099. <u>https://doi.org/10.1016/j.rse.2022.113099</u> © 2022, Elsevier. Licensed under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International <u>http://creativecommons.org/licenses/by-nc-nd/4.0/</u>

# 1 How much inundation occurs in the Amazon River basin?

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39

# 40 Abstract

41 The Amazon River basin harbors some of the world's largest wetland complexes, which are of major 42 importance for biodiversity, the water cycle and climate, and human activities. Accurate estimates of 43 inundation extent and its variations across spatial and temporal scales are therefore fundamental to 44 understand and manage the basin's resources. More than fifty inundation estimates have been generated for 45 this region, yet major differences exist among the datasets, and a comprehensive assessment of them is 46 lacking. Here we present an intercomparison of 29 inundation datasets for the Amazon basin, based on 47 remote sensing only, hydrological modeling, or multi-source datasets, with 18 covering the lowland 48 Amazon basin (elevation < 500 m, which includes most Amazon wetlands), and 11 covering individual 49 wetland complexes (subregional datasets). Spatial resolutions range from 12.5 m to 25 km, and temporal 50 resolution from static to monthly, spanning up to a few decades. Overall, 31% of the lowland basin is

51 estimated as subject to inundation by at least one dataset. The long-term maximum inundated area across 52 the lowland basin is estimated at 599,700  $\pm$  81,800 km<sup>2</sup> if considering the three higher quality SAR-based 53 datasets, and  $490,300 \pm 204,800$  km<sup>2</sup> if considering all 18 datasets. However, even the highest resolution 54 SAR-based dataset underestimates the maximum values for individual wetland complexes, suggesting a 55 basin-scale underestimation of  $\sim 10\%$ . The minimum inundation extent shows greater disagreements among 56 datasets than the maximum extent:  $139,300 \pm 127,800 \text{ km}^2$  for SAR-based ones and  $112,392 \pm 79,300 \text{ km}^2$ 57 for all datasets. Discrepancies arise from differences among sensors, time periods, dates of acquisition, 58 spatial resolution, and data processing algorithms. The median total area subject to inundation in medium 59 to large river floodplains (drainage area >  $1,000 \text{ km}^2$ ) is 323,700 km<sup>2</sup>. The highest spatial agreement is 60 observed for floodplains dominated by open water such as along the lower Amazon River, whereas 61 intermediate agreement is found along major vegetated floodplains fringing larger rivers (e.g., Amazon 62 mainstem floodplain). Especially large disagreements exist among estimates for interfluvial wetlands 63 (Llanos de Moxos, Pacaya-Samiria, Negro, Roraima), where inundation tends to be shallower and more 64 variable in time. Our data intercomparison helps identify the current major knowledge gaps regarding 65 inundation mapping in the Amazon and their implications for multiple applications. In the context of 66 forthcoming hydrology-oriented satellite missions, we make recommendations for future developments of 67 inundation estimates in the Amazon and present a WebGIS application (https://amazon-68 inundation.herokuapp.com/) we developed to provide user-friendly visualization and data acquisition of 69 current Amazon inundation datasets.

- 70 Key words: flooding, surface water, floodplains, interfluvial wetlands
- 71

73 Aquatic ecosystems cover extensive areas of the Amazon basin, and are associated with temporally 74 and spatially dynamic habitats such as floodable forests, savannas, grasslands, large and small 75 rivers, and lakes (Hess et al., 2015; Junk et al., 2011; Melack and Coe, 2021; Reis et al., 2019a). 76 These systems, hereafter called wetlands, support plants and animals that are adapted to the flood 77 pulse (Junk et al., 1989), play key roles in regional and global biogeochemical cycles, especially 78 the carbon cycle (Richey et al 1990; Dunne et al., 1998; Abril et al., 2014; Melack et al., 2004; Pangala et al., 2017; Martínez-Espinosa et al., 2020), and regulate the riverine transport of 79 80 dissolved and particulate material, including sediment and organic matter (Armijos et al., 2020; 81 Fassoni-Andrade and Paiva, 2019; Melack and Forsberg, 2001; Ward et al., 2017). Additionally, human settlements along Amazon wetlands (Blatrix et al., 2018; Denevan, 1996) benefit from 82 83 ecosystem services, including food provision from native plants and animals as well as crop and livestock production (Coomes et al., 2016; Jardim et al., 2020). 84

Many of the wetlands of the Amazon basin are considered floodplain because they are subject to seasonal or periodic inundation by river overflow (i.e., the flood pulse; Junk et al., 1989). The region also hosts large interfluvial wetlands, which unlike fringing floodplains along large rivers, are flooded mainly by local rainfall and runoff and characterized by shallow water (Belger et al., 2011; Bourrel et al., 2009; Junk et al., 2011). Water sources, inundation patterns, and geomorphology interact to determine the structure and function of these biodiverse ecosystems (Junk et al., 2011; Latrubesse, 2012; Park and Latrubesse, 2017).

92 The extent of inundated land (also called flooded land or surface water extent), and its temporal 93 variation, are core variables to understand wetland processes and are of interest for multiple 94 scientific disciplines, including ecology (Silva et al., 2013; Hawes et al., 2012; Luize et al. 2015), 95 land-atmosphere interactions (Prigent et al., 2011; Santos et al., 2019; Taylor et al., 2018), carbon

cycling and greenhouse gas emissions (Guilhen et al., 2020; Melack et al., 2004; Richey et al., 96 97 2002), and natural hazard management (Restrepo et al., 2020; Trigg et al., 2016). The Amazon 98 basin has been a focus for remote sensing developments and applications in hydrology (Fassoni-99 Andrade et al., 2021), especially for inundation estimation, given the basin's large scale and global 100 environmental relevance, relatively pristine landscape, and technical challenges posed by 101 persistent cloud cover (Asner, 2001) and dense vegetation. This resulted in the development of 102 more than 50 inundation maps and datasets for this region in recent decades. Tables 1 (datasets 103 used in this study) and S1 (datasets not used due to redundancy or unavailability) summarize most 104 of the datasets developed for mapping inundation in the Amazon basin.

105 Digital wetland maps were first produced for the Amazon basin by Matthews and Fung (1987) 106 from aeronautical charts. Optical remote sensing systems in the visible or thermal spectral range, 107 such as Landsat, are of limited value for most Amazon wetlands, since inundation under persistent 108 cloud cover and dense vegetation canopies can be difficult to detect. Because of this, microwave 109 systems have been employed. Large-scale inundation mapping was pioneered in the region through 110 analysis of Scanning Multi-channel Microwave Radiometer (SMMR) and Special Sensor 111 Microwave/Imager (SSM/I) passive microwave observations, which provided all-weather 112 capability and sensitivity to inundation even in the presence of partial vegetative cover (Hamilton 113 et al., 2002; Prigent et al., 2001; Sippel et al., 1998). Meanwhile, research demonstrated the all-114 weather capability and superior spatial resolution of synthetic aperture radar (SAR) systems. L-115 band SAR that can penetrate forest canopies and reveal underlying water through the "double 116 bounce" effect was shown to be promising for mapping inundation in the Amazon (Hess et al., 117 2003). More specifically, the high-resolution, dual-season classification of the Japanese Earth 118 Resources Satellite-1 (JERS-1) L-band SAR data for the entire lowland Amazon basin by Hess et al. (2015), validated with airborne videography images, has been used as a benchmark for the
inundation extent of Amazon wetlands. Since these initial studies, and with the availability of other
imagery (e.g., Advanced Land Observing Satellite (ALOS) 1 and 2 missions), the remote sensing
community seeking to map and characterize inundation employed various combinations of active
and passive microwave data to benefit from the higher spatial resolution of the former and the
higher temporal resolution of the latter (Aires et al., 2013; Jensen and McDonald, 2019; Papa et
al., 2010; Parrens et al., 2019, 2017; Prigent et al., 2007, 2020; Schroeder et al., 2015).

126 Besides the basin-scale mappings (which, in our context, refer to both basin-scale datasets and 127 those that cover only the lowland areas below 500 m.a.s.l. elevation) of annual maximum and 128 minimum inundation (Chapman et al., 2015; Hess et al., 2015; Rosenqvist et al., 2020), dynamic 129 datasets with high spatial and temporal resolution are mainly based on satellite passive microwave 130 observations of coarse spatial resolution (Global Inundation Extent Multi-Satellite – GIEMS), 131 Surface Water Microwave Product Series (SWAMPS), Surface Water Fraction (SWAF), Wetland 132 Area and Dynamics for Methane Modeling (WAD2M) datasets; see Table 1), which can be downscaled using ancillary data (Aires et al., 2017, 2013; Parrens et al., 2019). Basin-scale, 133 134 dynamic inundation estimates based on the ALOS satellite are limited given its low temporal resolution (repeat cycle of 46 days). Thus, some studies have analyzed time series of ALOS-135 136 Phased Array L-band Synthetic Aperture Radar (PALSAR) (Arnesen et al., 2013; Ferreira-Ferreira 137 et al., 2015) and ALOS-2 PALSAR-2 backscatter retrievals (Jensen et al., 2018) for subsets of 138 Amazon wetlands. However, with a few exceptions using subregional datasets (Arnesen et al., 2013; Ferreira-Ferreira et al., 2015; Hess et al., 2003; Jensen et al., 2018; Resende et al., 2019), in 139 140 situ validation of the basin-scale estimates has seldom been performed, given the remoteness of 141 much of the Amazon basin and the often dense forest cover, which hampers airborne monitoring142 of below-canopy inundation.

143 Complementary to the remotely sensed datasets, process-based hydrological models estimating 144 variables such as river discharge and flood extent have been developed and assessed from basin to 145 local scales in the major rivers of the basin (Beighley et al., 2009; Coe et al., 2008; Getirana et al., 146 2017, 2012; Hoch et al., 2017; Luo et al., 2017; Miguez-Macho and Fan, 2012; Paiva et al., 2013; 147 Yamazaki et al., 2011), thanks to the advent of new computational and modeling capabilities. Local-scale hydraulic models with coarse (Trigg et al., 2009; Wilson et al., 2007; Fleischmann et 148 149 al., 2020) and detailed input data (Ji et al., 2019; Pinel et al., 2019; Rudorff et al., 2014; Fassoni-150 Andrade, 2020) have further developed model capabilities for mapping inundation dynamics, especially for the floodplains fringing the Amazon mainstem. These models complement satellite-151 152 based flood mapping due to their higher temporal and spatial resolution, and capability to estimate 153 long-term time series, for both past and future (e.g., due to climate change) scenarios. The 154 understanding of their uncertainties can lead to optimal data fusion with satellite-based estimates, 155 such as considering multiple constraints within the water cycle representation (Pellet et al., 2021).

156 Among these numerous inundation datasets for the Amazon basin (Tables 1 and S1), divergences can be substantial due to the differences in sensor systems, timing, and data processing algorithms 157 158 (Aires et al., 2018; Fleischmann et al., 2020; Parrens et al., 2019; Pham-Duc et al., 2017; 159 Rosenqvist et al., 2020), and a comprehensive assessment of inundation estimates for the Amazon 160 is lacking. The need to compare different hydrological datasets for the Amazon has been recently 161 highlighted in the context of river discharge (Towner et al., 2019), precipitation (Wongchuig et al., 162 2017; Zubieta et al., 2019) and evapotranspiration (Paca et al., 2019; Wu et al., 2020). Meanwhile, 163 rapid environmental changes in the basin underscore the urgency for a better understanding of Amazon water resources (Fassoni-Andrade et al., 2021), for which management and planning can be hindered by the discrepancies among datasets. These questions regarding current data limitations in the largest basin in the world are also timely in anticipation of forthcoming hydrological satellite missions such as Surface Water and Ocean Topography (SWOT) and NASA-ISRO SAR (NISAR).

169 To better understand and quantify the state of understanding of inundation patterns in the Amazon 170 wetlands, we address the following questions: 1) How much Amazon land area is subject to 171 seasonal or permanent flooding, and how accurate are the estimates? 2) Which areas are in 172 particular disagreement and thus deserve further attention? 3) How do basin-scale estimates with 173 coarser resolution and less calibrated classification methods differ from those for individual 174 wetland complexes, with independent validation? 4) How do the various inundation estimation 175 approaches (optical imagery, SAR, passive microwave, hydrologic models) differ in terms of 176 inundation mapping and for different wetland types (e.g., floodplains and interfluvial areas)? In 177 order to answer these questions, we gathered 29 inundation datasets for the Amazon basin, 178 spanning a wide range of spatial (12.5 m to 25 km) and temporal (static, dual-season, monthly, 179 daily) resolutions, and coverages from the whole basin to individual wetland complexes (Table 1), 180 into a framework that provides a comprehensive assessment of current knowledge of Amazon 181 inundation.

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Table 1. List of 29 studies that mapped inundation over areas ranging from the entire Amazon basin to individual wetland complexes. These data sources were selected based on data availability and relevance for this intercomparison. In the case of hydrological models, time resolutions are the values assessed or provided by the models, which can be provided at finer time resolution if necessary, since many of them compute flood maps at daily or sub-daily time steps

- 187 and report time-integrated results. The column "Data type" refers to: OS: optical sensor; SAR: synthetic aperture
- 188 radar; HM: hydrological model; HR: multiple datasets at high resolution; CR: multiple datasets at coarse resolution.
- 189 The column "Type of inundation estimated" has three classes: "All", meaning both open water and vegetated wetlands,
- 190 "Open water", and "Wetland only (no open water)".

	Dataset name and						
	main mission/					Type of	
Data	model associated (if	Spatial	Temporal	Time		inundation	
type	applicable)	resolution	resolution	period	Region	estimated	Reference
				1992-			
CR	GIEMS-2	25 km	Monthly	2015	Basin	All	Prigent et al., 2020
				1992-			Jensen and McDonald,
CR	SWAMPS	25 km	Monthly	2020	Basin	All	2019
						Wetland	
						only (no	
				2000-		open	
CR	WAD2M	25 km	Monthly	2018	Basin	water)	Zhang et al., 2020
-				1993-			
HR	GIEMS-D3	90 m	Monthly	2007	Basin	All	Aires et al., 2017
			Static (max	1950-			
HR	CIFOR	232 m	inundation)	2000	Basin	All	Gumbricht et al., 2017
-				1992-			
HR	ESA-CCI	300 m	Annual	2015	Basin	All	Bontemps et al., 2013
			Monthly	1993-			Fluet-Chouinard et al.,
HR	GIEMS-D15	500 m	climatology	2004	Basin	All	2015
				1992-			
HR	GLWD	1 km	Static	2004	Basin	All	Lehner and Döll, 2004

	SWAF-HR / SMOS		Weekly to	2010-			
HR	mission	1 km	monthly	2020	Basin	All	Parrens et al., 2019
				1961-			
HM	THMB model	5-min	Monthly	2010	Basin	All	Coe et al., 2008
				1980-			
НМ	CaMa-Flood model	500 m	Monthly	2014	Basin	All	Yamazaki et al., 2011
				1980-			
HM	MGB model	500 m	Monthly	2015	Basin	All	Siqueira et al., 2018
				2006-			
HM	Bonnet model	180 m	Monthly	2019	Janauacá	All	Bonnet et al., 2017
	TELEMAC-2D			2006-			
HM	model	30 m	Monthly	2015	Janauacá	All	Pinel et al., 2019
	LISFLOOD-FP			1994-			
HM	model	90 m	Monthly	2015	Curuai	All	Rudorff et al., 2014
	G3WBM / Landsat		Static (open	1990-		Open	
OS	mission	30 m	water areas)	2010	Basin	water	Yamazaki et al., 2015
			Annual and				
	GLAD / Landsat		monthly	1999-		Open	
OS	mission	30 m	climatology	2018	Basin	water	Pickens et al., 2020
			Monthly				
	GSWO / Landsat		(cloud cover	1984-		Open	
OS	mission	30 m	may occur)	2019	Basin	water	Pekel et al., 2016
	Ovando / MODIS			2001-	Llanos de	Open	
OS	mission	500 m	8 days	2014	Moxos	water	Ovando et al., 2016
					Amazon		
	Park / MODIS		Monthly	2000-	River	Open	Park and Latrubesse,
OS	mission	230 m	climatology	2015	down-	water	2019

					stream of		
					Manaus		
			Max. and				
			min. annual				
			inundation				
	Hess / JERS-1		(dual	1995-	Basin		
SAR	mission	90 m	season)	1996	(lowlands)	All	Hess et al., 2003, 2015
	Chapman / ALOS-			2006-			
SAR	PALSAR mission	90 m	Monthly	2011	Basin	All	Chapman et al., 2015
			Max. and				
			min. annual				
	Rosenqvist /		inundation				
	ALOS-2 PALSAR-		(dual	2014-			
SAR	2	50 m	season)	2017	Basin	All	Rosenqvist et al., 2020
	Jensen / ALOS-2		Irregular (26	2014-	Pacaya-		
SAR	PALSAR-2 mission	50 m	images)	2018	Samiria	All	Jensen et al., 2018
	Arnesen / ALOS-		Irregular (12	2006-			
SAR	PALSAR mission	90 m	images)	2010	Curuai	All	Arnesen et al., 2013
	Ferreira-Ferreira /		Flood				
	ALOS-PALSAR		frequency	2007-			Ferreira-Ferreira et al.,
SAR	mission	12.5 m	only	2010	Mamirauá	All	2015
	Ovando-2 / ALOS-		Irregular (6	2006-	Llanos de		
SAR	PALSAR mission	100 m	images)	2010	Moxos	All	Ovando et al., 2016
	Pinel-2 / ALOS-		Irregular (16	2007-			
SAR	PALSAR mission	30 m	images)	2011	Janauacá	All	Pinel et al., 2019
	Resende / ALOS-		Static (max	2006-			
SAR	PALSAR mission	25 m	inundation)	2011	Uatumã	All	Resende et al., 2019

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### 193 **2. Methodology**

# 194 **2.1 Study area**

The Amazon basin spans around 6 million km<sup>2</sup> in nine South American countries (Figure 1), with 195 high annual rainfall (~2,200 mm year<sup>-1</sup>), and the Amazon River discharge makes a major 196 197 contribution to global freshwater and sediment exports to the ocean (Fassoni-Andrade et al., 2021). 198 We delineated the catchment area upstream from Gurupá city, within the tidal river ~390 km from 199 the ocean; hence not including the Tocantins-Araguaia basin and parts of the Amazon estuary and 200 Marajó Island. We selected the 5.11 x  $10^6$  km<sup>2</sup> of Amazon lowlands defined as areas lower than 201 500 m elevation based on the Shuttle Radar Topography Mission Digital Elevation Model (SRTM 202 DEM) for the area of dataset comparisons in our study. This decision is consistent with several 203 studies limited to lowlands because of the limitations of certain methods in estimating flooding in 204 mountainous terrain (Hess et al., 2015).

In addition to basin-scale datasets, estimates of inundated areas for 11 individual wetland complexes (also referred to as "subregional") in the Amazon basin were analyzed, including seven areas for which more detailed estimates were available. This was performed to understand how the basin-scale datasets may vary in accuracy across different wetland types (Figure 1): Curuai floodplain lake (Arnesen et al., 2013; Rudorff et al., 2014), Janauacá floodplain lake (Bonnet et al., 2017; Pinel et al., 2019), Uatumã river floodplain (Resende et al., 2019), Mamirauá Reserve (Ferreira-Ferreira et al., 2015), Pacaya-Samiria wetlands (Jensen et al., 2018), Llanos de Moxos 212 wetlands (Ovando et al., 2016), lower Amazon floodplain (Park and Latrubesse, 2019), Amazon 213 mainstem floodplain (from Iquitos to Gurupá), Purus floodplain, Roraima savannas, and Negro 214 savannas. A brief summary of these wetlands is provided in supplementary Table S2, and their 215 main features are summarized in the following. Curuai is representative of the shallow lakes in the 216 lower Amazon floodplain. It is separated from the river by narrow levees (Rudorff et al., 2014) 217 and has a high suspended sediment concentration. Janauacá is typical of the middle Amazon River 218 floodplain, and is composed of a ria lake (i.e., a blocked valley lake with relatively sediment-free 219 waters; Latrubesse (2012)) and "várzea" environments (white-water floodplains) in its northern 220 part (Pinel et al., 2019). Uatumã River is an Amazon tributary with black-water floodplain 221 ("igapó"), and includes the Balbina hydroelectric reservoir, operating since 1987, which affects 222 the river's hydrological regime (Schöngart et al., 2021). The Uatumã floodplain reach assessed 223 here is the 300-km reach between Balbina dam and the confluence with the Amazon River. The 224 Mamirauá Sustainable Development Reserve is located in the confluence between Solimões and 225 Japurá rivers, and is characterized by a mosaic of "chavascal", herbaceous, and low and high 226 várzea vegetation (Ferreira-Ferreira et al., 2015). The Purus River is a major tributary, and its 227 floodplain was chosen because of its large floodplain to river width ratio. Pacaya-Samiria wetlands 228 are composed of flooded forests, palm swamps and peatlands in the upper Solimões River (Draper 229 et al., 2014; Lähteenoja et al., 2012). The Llanos de Moxos floodable savannas occupy the 230 interfluvial areas between the Beni, Mamoré and Madre de Dios rivers in the upper Madeira basin 231 (Hamilton et al., 2004). The Negro savannas, locally known as "campina wetlands" and 232 "campinarana wetlands", depending on the vegetation density, are thought to have formed from 233 regional neotectonic depressions and were called the "Septentrional Pantanal" given their large 234 area (Rossetti et al., 2017a, 2017b; Santos et al., 1993). The Roraima floodable savannas extend from Roraima State in Brazil to the Rupununi savannas in Guyana, and comprise mainly smaller
river floodplains interspersed with poorly drained interfluvial savannas subject to flooding by local
rainfall (Hamilton et al., 2002); here we only considered the Roraima wetlands in the upper Branco
River basin, which is within the Amazon basin.

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Figure 1. The Amazon basin and its major wetland systems: (a) Amazon basin delineation (red lines) over the countries
of South America (black lines). (b) Land cover based on a 2010 map from the European Space Agency Climate Change
Initiative (ESA-CCI) (Bontemps et al., 2013), showing the distribution of forest and savanna across the basin, as well
as large floodplains (see methodology section 2.3). (c) Basin distribution of major wetland systems showing locations

of interest for this study. Elevations lower than 500 m are shown in grey (based on SRTM DEM). The orange polygons
show the areas for which a subregional dataset was available for this study (Figure 4), and the green ones show wetland
areas of interest that do not have datasets specifically designed for these subregions. Photos depicting different wetland
complexes for (d) Mamirauá (courtesy of João Paulo Borges Pedro), (e) Llanos de Moxos (courtesy of Alex Ovando),
(f) Cabaliana floodplain lake close to Manacapuru (courtesy of Stephen Hamilton), and (g) Pacaya-Samiria (courtesy
of Katherine Jensen) regions, respectively.

251

# 252 **2.2 Datasets**

253 Twenty-nine inundation datasets covering areas ranging from the whole-basin scale to individual 254 wetland complexes, based on multiple data sources and spatiotemporal resolutions, were 255 assembled for our comparison (Table 1). Most of these datasets are recent, with 18 out of the 29 256 published since 2016, and 27 since 2011. They were chosen due to data availability and 257 representativeness; other datasets that were either unavailable or methodologically redundant to 258 those in our comparison were not used but are catalogued in Table S1. Overall, there are eight 259 dynamic (weekly to monthly; Figure 2) and 10 static (which include long-term maximum, annual 260 or dual-season categories; Figure 3) basin-scale datasets.



Figure 2. Basin-scale, dynamic inundation datasets used in this study, divided into three classes (hydrological models; merging of multiple datasets at high resolution; merging of multiple datasets at coarse resolution). Long-term flood frequency maps are provided for each dataset, calculated as the percentages of observations labelled as flooded throughout the entire time-series.



Figure 3. Basin-scale, static or dual-season inundation datasets used in this study, divided into three classes (merging of multiple datasets at high resolution; based on optical sensors; and based on SAR data). Flood frequency maps are not provided because the datasets are mainly static or annual-based.

Passive microwave (PM) data are the basis of SWAF-HR, GIEMS family (GIEMS-D15, GIEMS-D3, GIEMS-2), and SWAMPS, while ancillary data (i.e., optical imagery and microwave scatterometry) are used to complement the PM signal. SWAF-HR data result from the disaggregation of water surface fraction in a dataset at coarser spatial resolution (SWAF), based on L-band passive microwave observations from the Soil Moisture and Ocean Salinity (SMOS) satellite (Parrens et al. 2017). The disaggregation of SWAF relies on water occurrence maps from

279 GSWO and the Digital Elevation Model (DEM) Multi-Error-Removed-Improved-Terrain 280 (MERIT) (Parrens et al., 2019). A global implementation of SWAF based on multi-angular and 281 multi-polarization information has also been implemented (Al Bitar et al. 2020). GIEMS merges 282 multiple satellite passive and active microwave observations, along with the optically-derived 283 NDVI (Normalized Difference Vegetation Index), to detect the surface water and estimate the 284 vegetation attenuation, for a monthly quantification of the surface water extent at  $\sim 25$  km spatial 285 resolution (Prigent et al., 2001, 2007, 2020; Papa et al., 2010). It is further disaggregated at 90-m 286 resolution (GIEMS-D3) using a topographical downscaling methodology (Aires et al. 2017).

Three basin-scale datasets are based mainly on SAR data from JERS-1 (Hess et al., 2003, 2015), and its successor missions ALOS-PALSAR (Chapman et al., 2015) and ALOS-2 PALSAR-2 (Rosenqvist et al., 2020). These three datasets cover different decades of observation but are methodologically similar.

291 Three of the optical-based datasets are based on Landsat data: GSWO (Pekel et al., 2016), 292 G3WBM (Yamazaki et al., 2015) and GLAD (Pickens et al., 2020). Although GSWO and GLAD 293 can provide monthly estimates for the Landsat archive (1984-today), given the inability of optical 294 data to estimate flooding under cloud cover or dense vegetation canopies, only annual maximum 295 and minimum values are used. For GLAD and GSWO, we consider a threshold of occurrence of 296 surface water of 95% to estimate the minimum inundation (i.e., for the permanently inundated 297 areas; Aires et al., 2018); otherwise, only a few isolated open water areas would be considered for 298 the minimum extent.

The European Space Agency Climate Change Initiative dataset (ESA-CCI) is based on surface
reflectance from MERIS, the Advanced Very High-Resolution Radiometer (AVHRR) and

301 PROBA-V data and Global Water Bodies from the Envisat Advanced Synthetic Aperture Radar
302 (ASAR) (Bontemps et al., 2013). Since the wetland pixels in ESA-CCI varied negligibly
303 throughout the years of observations, we use only the 2010 dataset as the ESA-CCI estimate for
304 maximum inundation.

305 Another set of data is based on the merging of multiple global datasets: GLWD, GIEMS-D15 and 306 WAD2M. GLWD is one of the first globally consistent databases of wetlands, which was based 307 on a collection of wetland estimates from diverse institutions worldwide (Lehner and Döll, 2004). 308 GIEMS-D15 combines GLWD, the Hydrosheds drainage network, and Global Land Cover 2000. 309 WAD2M is based on SWAMPS and CIFOR within its merging framework. WAD2M is the only 310 dataset to exclude open water areas (removal based on GSWO) due to its goal of estimating 311 wetland methane emissions. SWAF-HR (Parrens et al., 2019) and GIEMS-D3 (Aires et al., 2017) 312 use additional data and methodologies to downscale the original 25-km passive microwave-based 313 SWAF (Parrens et al., 2017) and GIEMS (Papa et al., 2010; Prigent et al., 2007) datasets to 1 km 314 and 90 m, respectively. While GIEMS-D3 has a different inundation magnitude than the original 315 GIEMS due to merging with ancillary data, SWAF-HR conserves the same inundation magnitude 316 across scales.

Among hydrological models, we selected representative datasets from each of the following broad modeling types: 1) process-based hydrologic models that use flood routing to represent inundation processes (i.e., from a simple kinematic wave model coupled to an inundation method to more complex flow routing methods); or 2) hydraulic (or hydrodynamic) models that consider the shallow water equations (or its simplifications) at any dimension (1D, 2D or 3D). For our analysis, we adopted two basin-scale models – one hydrologic (THMB; Coe et al. (2008)) and one hydrologic-hydrodynamic (MGB, Siqueira et al. (2018)), as well as a global-scale hydrodynamic

324 model (CaMa-Flood, Yamazaki et al. (2011)), in the Earth2Observe version available at 325 <http://www.earth2observe.eu/>). The inundated area estimation is largely affected by the DEMs. 326 The DEMs adopted in the model runs were: Bare-Earth (O'Loughlin et al., 2016) for MGB, 327 MERIT (Yamazaki et al., 2017) for CaMa-Flood, and SRTM (Farr et al., 2007) for THMB. The 328 rainfall/runoff input data are MSWEP v.1.1 daily precipitation (Beck et al., 2017) for MGB, 329 HTESSEL daily runoff (Balsamo et al., 2009) for CaMa-Flood, and CRU TS v.3.2.1 monthly 330 precipitation (Harris et al. 2014) for THMB. Although other hydrologic models have been applied 331 to the Amazon basin (Tables 1 and S1), the models chosen here were selected as representative of 332 global to local models, for having been well validated and applied over the Amazon basin, and for 333 representing state-of-the-art Amazon hydrologic modeling. All basin-scale models represent one-334 dimensional (1D) flows only (i.e., floodplains are represented as storage units without active flow), 335 and thus do not represent 2D surface flows that occur in wetlands (Alsdorf et al., 2007; 336 Fleischmann et al., 2020). A detailed comparison of model capabilities and structural uncertainties 337 is beyond our current scope. Hydrologic models have different temporal resolution depending on 338 their numerical stability and forcing data. For instance, MGB and CaMa-Flood models run at an 339 adaptive time step (sub-minute timestep in the case of MGB), but are assessed at daily resolution 340 given their daily precipitation forcing. We aggregated the models' estimates to monthly averages 341 to make them comparable to the remote sensing dynamic datasets.

The datasets available for individual wetland complexes are presented in Figure 4. ALOS-2 PALSAR-2 data were used for the Pacaya-Samiria region (Jensen et al., 2018), and the ScanSAR mode of ALOS/PALSAR for the following datasets: Curuai floodplain lake (Arnesen et al., 2013), Mamirauá Reserve (Ferreira-Ferreira et al., 2015), Uatumã river floodplain (Resende et al., 2019), and Janauacá floodplain lake (Pinel et al., 2019). MODIS optical data were used for the Llanos de

Moxos savannas in the upper Madeira River basin (Ovando et al., 2016) and the lower Amazon floodplain (Park and Latrubesse, 2019). Two local-scale 2D hydraulic models (LISFLOOD-FP for Curuai lake, Rudorff et al. (2014), and TELEMAC-2D for Janauacá lake, Pinel et al. (2019)), and one local-scale hydrologic model (for Janauacá lake; Bonnet et al. (2017)) were considered; together, these are representative of the state-of-the-art of hydrological modeling in Amazon wetlands.

The datasets were stored in various formats (i.e., raster and polygon shapefiles) and projections (mainly projected UTM and geographic coordinate system with WGS84 datum), and were converted to the WGS84 geographic coordinate system to compute areas. SWAMPS was provided at the Equal-Area Scalable Earth (EASE) Grid, which was used to estimate its flooded areas. Hydrologic model outputs were provided as either binary inundation maps or flood depth raster files, which were then converted into binary maps by assuming depth > 0 m as inundated pixels.



361 Figure 4. Long-term flood frequency maps from subregional inundation datasets (i.e., for individual wetland 362 complexes) used in this study. The Uatumã dataset (2) is static and is displayed as the maximum extent. Flood 363 frequency maps are produced by computing the long-term average of all inundation maps available for each dataset.

364

# 365 2.3 Comparison framework

The comparison framework involved the following analyses, considering the entire basin and 11 wetland complexes (seven areas with available subregional estimates, and four additional areas of interest without subregional estimates; Figure 1):

369	•	Annual maximum and minimum inundation estimates for each of the 18 basin-scale
370		datasets (section 3.1);
371	•	Basin-scale, long-term maximum and minimum inundation estimates for each of the 18
372		basin-scale datasets (section 3.1);
373	•	Long-term maximum and minimum inundation estimates for each of the 18 basin-scale
374		and 11 subregional datasets (section 3.2);
375	•	Comparison between basin-scale and subregional datasets with temporal (nRMSD and
376		Pearson correlation) and spatial (Fit metric) assessment (section 3.2);
377	٠	Assessment of spatial agreement among the 18 basin-scale datasets at 1 km, for both long-
378		term maximum and minimum inundation maps (section 3.3);
379	•	Estimation of long-term maximum inundation for two classes of wetlands for the entire
380		basin: (i) medium to large river floodplains and (ii) interfluvial wetlands and small
381		floodplains (section 3.4).
382		

The long-term maximum and minimum inundation extents were computed for each dataset as the area of all pixels that were inundated at least once in the whole monthly time series, for the maximum, and as those pixels that were always inundated, for the minimum. We stress that analyzing long-term changes in inundation patterns is beyond the scope of this study, and thus we assumed stationarity in our comparisons of long-term maximum and minimum inundation extents from different time-periods.

The agreement of all basin-scale, high-resolution datasets (i.e., all basin-scale ones except for THMB, GIEMS-2, SWAMPS and WAD2M, which have a coarse resolution between 9 and 25 391 km) was assessed for long-term maximum and minimum inundation at 1 km resolution, which is 392 the resolution of SWAF-HR, the coarsest resolution among the high-resolution datasets. For each 393 1 km pixel, the total number of datasets agreeing that it was inundated (either for maximum or 394 minimum extent) was computed, following Trigg et al. (2016). Given the size of the Amazon basin, 395 a 1 km resolution was considered adequate for the analysis. The analysis was done by aggregating 396 all datasets to 1 km, and considering that a 1 km pixel is flooded if more than 50% of its area is 397 flooded (following Hamilton et al., 2002). A sensitivity test was performed using a 25% threshold 398 and led to similar conclusions at the whole basin scale (Figure S1).

399 The basin-scale and four additional subregional datasets were compared to seven subregional ones, 400 which were used as independent validation datasets, and cover the following sites: Curuai 401 (Arnesen et al., 2013), Uatumã (Resende et al., 2019), Janauacá (Pinel et al., 2019), Mamirauá 402 (Ferreira-Ferreira et al., 2015), Pacaya-Samiria (Jensen et al., 2018), Llanos de Moxos MODIS 403 (Ovando et al., 2016) and lower Amazon River (Park and Latrubesse, 2019). Varying degrees of 404 validation exercises were performed for these validation datasets, with some being extensively 405 validated with airborne videography (Hess et al., 2003) or local surveys (Arnesen et al., 2013; 406 Ferreira-Ferreira et al., 2015; Jensen et al., 2018; Resende et al., 2019), while others were assessed 407 through comparisons with other datasets (Pinel et al., 2019), or visually inspected, as in the large 408 domains of the Llanos de Moxos (Ovando et al., 2016) and lower Amazon River (Park and 409 Latrubesse, 2019) subregional datasets. The four additional subregional datasets are: Curuai 410 LISFLOOD-FP model (Rudorff et al., 2014), Janauacá hydrological model (Bonnet et al., 2017), 411 Janauacá TELEMAC-2D model (Pinel et al., 2019), and Llanos de Moxos ALOS-PALSAR 412 (Ovando et al., 2016).

413 To use the subregional studies to assess the accuracy of the datasets covering broader areas, the 414 basin-scale and four additional subregional datasets were compared to the subregional validation 415 datasets at monthly temporal resolution, considering the total inundated area per wetland area (i.e., 416 the whole Curuai Lake domain, the whole Uatumã floodplain, and so forth). The polygons of each 417 wetland area, which were used to extract the information from the basin-scale datasets, were 418 delineated as a 1-km buffer around the maximum inundated area, according to each subregional 419 dataset. For the four areas of interest without subregional datasets (Amazon mainstem and Purus 420 floodplains, and Roraima and Negro wetlands), the polygons were created considering the 421 maximum lateral extent in accordance with the MERIT DEM (Yamazaki et al., 2017) and ESA-422 CCI land cover for savannas. The time series were compared with Pearson linear correlation (R) 423 and the normalized root mean square deviation (nRMSD), computed as the RMSD between a given 424 inundation map and the subregional validation map (i.e., the individual wetland complexes) 425 divided by the subregional long-term average inundation. The term 'deviation' was preferred over 426 'error' to stress the uncertainties inherent to all datasets, for both basin and subregional scales, 427 although those derived for an individual wetland complex are considered as superior in accuracy 428 for having a more dedicated data processing for that particular area, and being validated with 429 ground surveys in some cases.

The ability of a particular dataset to estimate the local spatial patterns at maximum inundation was
assessed with the Fit metric (Bates and De Roo, 2000), which has been successfully applied to
compare inundation datasets (Bernhofen et al., 2018), and is computed as:

$$Fit = 100\% * \frac{A \cap B}{A \cup B}(1)$$

Where A and B are the subregional validation dataset estimates (e.g., the subregional map thatcorresponds to maximum inundation) and the basin-scale maximum inundation maps.

436 To assess different wetland environments, we differentiate medium to large river floodplains from 437 interfluvial wetlands and small floodplains. An estimation of the total flooded area of large river 438 floodplains was computed, considering river reaches with upstream drainage area larger than 1,000 439 km<sup>2</sup>, and a buffer mask around the river reaches (mask presented in Figure 1). The buffer was 440 defined based on the Hydrosheds drainage network (Lehner and Grill, 2013), segmented into 15 441 km-long reaches as in Siqueira et al. (2018). The buffer was proportional to the local reach drainage 442 area and further manually adjusted to include the maximum floodplain lateral extent, as estimated 443 from a visual inspection of the MERIT DEM (Yamazaki et al., 2017) and the three basin-scale 444 SAR-based datasets (Hess, Chapman and Rosenqvist datasets). Buffer values varied from 4 km in 445 upper reaches to 150 km on the Amazon mainstem close to the Mamirauá Reserve. Estimating 446 floodplain total inundated area is relevant to differentiate the Amazon riverine fringing floodplains 447 from non-floodplain wetlands (here referred to as interfluvial wetlands).

Finally, in order to assess the current capabilities of basin-scale mapping of inundation dynamics
at high spatial and temporal resolution, a further assessment of the four high-resolution dynamic
datasets (GIEMS-D3, CaMa-Flood, SWAF-HR and MGB) at their native resolutions was
performed by computing their long-term flood frequency for the entire basin.

452

#### 453 **3. Results and Discussion**

#### 454 **3.1** How much inundation is estimated to occur in the Amazon basin?

Comparisons among the various estimates of inundation area can begin with the maximum and 456 457 minimum inundated area across the entire Amazon basin. We found wide variation in the annual 458 maximum and minimum inundation estimates for the entire basin scale (Figure 5), as well as the 459 long-term maxima and minima (Figure 6 and Table 2). The annual maximum inundation area 460 represents the total area subject to inundation at some point over the year, whereas the annual 461 minimum inundation area represents the area that remained inundated all year. SAR estimates, 462 especially those based on L-band sensors and those having undergone validation (i.e., the Hess et 463 al. (2003) dataset), are assumed to be the most accurate given their high spatial resolution and 464 capability of mapping flooded areas under dense vegetation canopies and cloud cover. Given the 465 lack of ground validation for most basin-scale datasets, we assess their accuracy by comparing 466 them to subregional validation datasets in section 3.2.

467 By computing means and standard deviations of the long-term maximum area subject to inundation by type of data (Table 2), we obtain the following values:  $138,200 \pm 45,300 \text{ km}^2$  (mean  $\pm$  S.D.) for 468 469 optical,  $533,500 \pm 217,800$  km<sup>2</sup> for multiple datasets at high resolution,  $579,100 \pm 108,900$  km<sup>2</sup> 470 for those at coarse resolution,  $542,800 \pm 80,600$  km<sup>2</sup> for hydrological models, and  $599,700 \pm$ 471 81,800 km<sup>2</sup> for SAR. The mean area for optical-based datasets is thus around 23% of the SAR-472 based estimate. If we assume that the ensemble of datasets could be a proxy of inundation 473 uncertainty in the Amazon basin, and neglecting the optical and land cover-based data (G3WBM, 474 GLAD, GSWO and ESA-CCI) and CIFOR datasets, given their lower capability to map inundation 475 as discussed below, 13 datasets are left, yielding an estimation for the long-term maximum 476 inundation of 559,300  $\pm$  81,100 km<sup>2</sup>. This value is around 40,000 km<sup>2</sup> lower than the mean of the 477 maximum inundation area from the three SAR datasets. The mean of the maximum inundation area considering all 18 datasets is  $490,300 \pm 204,800 \text{ km}^2$ . Compared to the maximum inundation area, the relative deviation among available estimates is higher for the long-term minimum area inundated —125,900 ± 77,600 km<sup>2</sup> (mean ± S.D.), with a coefficient of variation of 0.62, for the 12 basin-scale datasets that provide minimum area, and 139,300 ± 127,800 km<sup>2</sup> for the three SARbased datasets, with a coefficient of variation of 0.92.

483 None of the datasets can map small, narrow floodplains or riparian zones, for which only simple 484 calculations are currently available (e.g., Junk et al., 1993), and whose total area can only be 485 estimated through statistical extrapolation of observable rivers. These small zones contribute to 486 the overall uncertainties of the inundation estimates. For instance, a wetland mask developed by 487 Hess et al. (2015) for SAR-based wetland classification yielded a basin-scale estimation of wetland 488 area including the smallest floodplains of 840,000 km<sup>2</sup>. This estimate is much larger than the 489 largest long-term maximum inundated area obtained with SAR data (659,100 km<sup>2</sup> with 490 Rosenqvist's dataset). In section 3.2, it will be shown that almost all datasets tend to underestimate 491 the maximum inundation, when compared to subregional ones. The two SAR-based datasets with 492 highest accuracy underestimate maximum inundation by 9% (Rosenqvist) and 13% (Hess), based 493 on the average difference between these and the subregional estimates for the seven locations with 494 available data. If this holds true for the whole basin, the basin-scale maximum inundation would 495 be around 10% higher.

496

# 497 3.1.2 Estimates based on SAR datasets

498 At the basin scale, SAR-based estimates of maximum annual inundation range from 424,600 km<sup>2</sup>
499 (Rosenqvist) to 633,500 km<sup>2</sup> (Hess), and minimum inundation from 53,900 km<sup>2</sup> (Rosenqvist) to

500 284,200 km<sup>2</sup> (Hess), as shown in Figure 5. By considering long-term maximum inundation (i.e., 501 all pixels that were inundated at least once in the entire available time series), instead of annual 502 maxima, the SAR-based estimates range from 506,400 km<sup>2</sup> (Chapman) to 659,100 km<sup>2</sup> 503 (Rosenqvist) for the entire basin (Table 2). The minima vary from 42,400 km<sup>2</sup> (Rosenqvist) to 504 284,200 km<sup>2</sup> (Hess). This highlights the large differences that exist, especially for the minima, 505 usually referred to as the "low-water period." Chapman's dataset, based on the 2006-2011 ALOS-506 PALSAR archive, has a smaller total maximum inundation area than the other two SAR datasets, 507 as well as a smaller estimate for minimum inundation in relation to Hess' estimate, which in turn 508 was developed from SAR mosaics at two seasons spanning only (1995 - 1996).one year 509 Differences among the three datasets may originate from differences in acquisition dates, 510 interannual and seasonal inundation variability, algorithms, spatial resolutions, or inconsistencies 511 regarding the data processing. For example, Chapman estimates long-term maxima and minima 512 based on multiple years, while Hess and Rosenqvist provide annual values. The calibration 513 uncertainty was also higher for the JERS-1 data used in Hess' mapping than in the subsequent 514 satellites (ALOS-PALSAR and ALOS-2 PALSAR-2) (Hess et al., 2003). For long-term minimum 515 inundation, the interannual variability seems to be a minor factor since the Hess dataset, which 516 estimated a larger figure than the other ones, was developed for a year with minimum water levels 517 higher than those during Chapman's acquisition dates, but lower than those during Rosenqvist's 518 ones (see Fig. 8 in Rosenquist et al., 2020). Thus, the larger minimum inundation extent by Hess 519 et al. (2015) seems to be more related to algorithm differences (Figure S2). For the maximum 520 water levels, Hess' period was associated with an average year, below the water levels in Chapman 521 and Rosenqvist, and this may explain the relatively higher long-term maximum inundation by 522 Rosenqvist, while Chapman's smaller values are likely due to algorithm differences. For the

western basin, Hess' estimate is based on JERS-1 data mostly from June 1996 (Hess et al., 2015), which likely missed some of the inundation in this region as in the Pacaya-Samiria region, and may partly explain the larger value by Rosenqvist (see section 3.2.2). Spatial resolution is also an important factor: Rosenqvist's resolution is 50 m, and it is capable of representing smaller floodplains than the other two (Figure S3), as will be discussed in section 3.2.2.

528

#### 529 3.1.3 Assessment of other datasets

530 The coarse-resolution datasets and hydrologic models generally estimate smaller annual maximum 531 inundation areas in comparison to the SAR datasets, with the exception of SWAF-HR, WAD2M 532 and CaMa-Flood that yield similar annual maximum inundation. This results from the low 533 sensitivity of the passive microwave signal, which underlies most coarse-resolution datasets, to 534 detect small fractional flooded areas within the grid cells, flooding under particularly dense 535 vegetation, and flooding of short duration (i.e., less than one month of consecutive inundation) 536 (Hamilton et al., 2002). The higher sensitivity of the SWAF-HR may be associated with the use of 537 L-band passive microwave emission. Given the long-term data availability from dynamic, coarse-538 resolution datasets, their long-term mean estimates are closer to the SAR ones, varying from 539 450,800 km<sup>2</sup> (THMB) to 630,900 km<sup>2</sup> (SWAF-HR), when compared to the annual scale analysis. 540 Therefore, no clear relationship between long-term minimum or maximum inundation and the 541 spatial resolution of the datasets is observed (Figure 6), which could be expected when analyzing 542 the annual values (Figure 5).

As expected, the optical-based datasets (GSWO, G3WBM, GLAD) cannot map inundation under
dense vegetation canopies and thus lead to much lower estimates of basin-wide inundation area

545 (Aires et al., 2018; Parrens et al. 2017). Similarly, ESA-CCI, which is based on land cover 546 classification of optical imagery with the addition of SAR inputs for delineation of wetland areas, 547 yields low basin-wide inundation areas, although relatively higher than the purely optical-based 548 estimates. In contrast, the multi-satellite-based CIFOR provides an unrealistically large estimate 549 of maximum inundation area (872,700 km<sup>2</sup>), which may be due to overestimation of soil moisture by the topographic index used. This method is sensitive to rainfall overestimation, which may have 550 551 occurred in 2011, the year for which CIFOR was developed (Gumbricht et al., 2017). While the 552 dataset does represent well the spatial extent of peatlands across the Pacaya-Samiria region 553 (Gumbricht et al., 2017), its estimation of widespread inundation across the basin has limitations 554 to represent the large Amazon river floodplains, especially the forested ones, which are classified as "swamps (including bogs)" by this dataset together with extensive interfluvial areas (Figure S4). 555



Figure 5. (a) Annual maximum and minimum flooded areas for the Amazon basin (< 500 m in elevation) for 18 basin-</li>
scale datasets over their respective observation time periods. Note that some datasets provide only average estimates
based on multiple years of observation (e.g., GLWD, Chapman, G3WBM), and are marked as horizontal lines for the
period of observation.



Figure 6. Summary of long-term (a) minimum and (b) maximum inundation for the 18 basin-scale datasets, which are categorized into five types (optical data; combination of datasets at high resolution; combination of datasets at low resolution; synthetic aperture radar; and hydrological models). Estimates by dynamic datasets are not directly comparable to the static ones; thus, each is colored differently: red (dynamic) and black (static). Legend for dataset types: OS: Optical Sensor; SAR: Synthetic Aperture Radar; HM: Hydrological Model; HR: multiple datasets at High Resolution; CR: multiple datasets at Coarse Resolution.

571 Table 2. Basin-scale, long-term minimum and maximum inundation estimates for 18 datasets.

	Dataset	Minimum (km²)	Maximum (km²)
Multiple datasets at coarse resolution	GIEMS-2	45,800	486,600
	SWAMPS	157,400	491,100
	WAD2M	225,500	707,900
Multiple datasets at high resolution	GIEMS-D3	116,600	500,700
	CIFOR	-	872,700
	ESA-CCI	-	267,400
	GIEMS-D15	157,700	545,400
	GLWD	-	481,200

	SWAF-HR	53,200	630,900
Hydrological model	THMB	65,200	450,800
	CaMa-Flood	188,100	576,700
	MGB	83,600	600,900
Optical sensor	G3WBM	-	98,500
	GLAD	25,700	187,600
	GSWO	37,000	128,500
Synthetic Aperture Radar	Hess	284,200	633,500
	Chapman	91,200	506,400
	Rosenqvist	42,400	659,100

572

# 573 3.2 How much inundation is estimated to occur in individual wetland regions?

# 574 3.2.1 Overall assessment

The 18 basin-scale inundation datasets were compared with the 11 subregional ones through analysis of long-term means of annual maximum inundated areas (Table 3), long-term means of annual minimum areas (Supplementary Table S3), and multiple comparison metrics (Supplementary Table S4). The subregional datasets, covering individual wetland complexes, are considered as independent validation datasets, given the ground validation performed for most of them, as well as the use of a region-specific classification, and the often higher spatial resolution (e.g., 12.5 m for some based on ALOS-PALSAR imagery).

582 The Amazon River floodplains (from Iquitos to Gurupá) and the Llanos de Moxos regions are the 583 largest Amazon wetland complexes:  $106,800 \pm 25,800$  km<sup>2</sup> and  $113,500 \pm 53,400$  km<sup>2</sup>, respectively

when considering the three SAR-based datasets, and  $94,100 \pm 32,500 \text{ km}^2$  and  $85,300 \pm 52,400$ 

585 km<sup>2</sup> when considering all 18 basin-scale datasets. Besides these two areas, the third largest 586 Amazon wetland region is Pacaya-Samiria, with 29,700  $\pm$  20,600 km<sup>2</sup> (all datasets) and 40,000  $\pm$ 587 4,200 km<sup>2</sup> (SAR datasets).

588 The comparison of the long-term means of annual maximum and minimum observed inundation 589 over the available time periods indicates differences between basin-scale datasets and the 590 subregional validation datasets. Overall, the subregional datasets had a larger maximum inundation 591 extent than that estimated for the subregion from the basin-scale datasets. The underestimation by 592 the basin-scale ones varied from 49% for the Pacaya-Samiria region to 5% for the lower Amazon 593 River floodplain. Only three datasets overestimated the maximum extent of inundation: GIEMS-594 D3, GIEMS-D15 and GLWD. The basin-scale, SAR-based ones (Hess, Chapman and Rosenqvist) 595 underestimated the maximum extent in the regions represented by all subregional datasets, except 596 Rosenqvist for Janauacá Lake, and Hess for the Llanos de Moxos region. This is likely related to the higher resolution of many of the subregional datasets (e.g., 12.5 m original and 25 m final 597 598 resolution for the Uatumã ALOS-PALSAR classification by Resende et al., 2019), differences in 599 image acquisition period, and fine-tuning that may occur with dedicated processing for a particular 600 region.

To investigate the depiction seasonal patterns of inundation by the various datasets, we assessed the correlation between the time series of absolute inundated areas from the dynamic ones and the estimates for individual wetland complexes (Table S3). Overall, all datasets agreed well (average Pearson correlation larger than 0.63 for the four wetland complexes with available time series), showing a similar depiction of the inundation seasonality. However, their ability to monitor highresolution flood frequency is limited, as will be further discussed in section 4. A visual comparison of the time series (Figure S6) shows agreement on seasonal timing of flooding and drainage, but
disagreement in the extent of inundation. In particular, two datasets have a small overall annualamplitude (SWAMPS and WAD2M).

610 Overall, four datasets had the best overall representation of spatial patterns in inundation (Fit 611 metric; see Equation 1), as analyzed at 1 km pixel resolution, in comparison to the subregional 612 validation datasets: Hess, GLWD and the two hydrodynamic models (MGB and CaMa-Flood), 613 which were associated with average Fit metric between 0.64 and 0.67 (Table S3). While hydrologic 614 models such as MGB, CaMa-Flood and THMB have a satisfactory agreement basin wide, they are 615 unable to represent wetlands not primarily inundated by rivers (Fleischmann et al., 2020; Zhou et 616 al., 2021). For example, the Llanos de Moxos inundation is underestimated by both CaMa-Flood 617 and MGB with low Fit metric values (0.19-0.28; Table S3). This is expected for interfluvial wetlands such as Llanos de Moxos and Roraima, where much of the flooding is caused by poor 618 619 drainage of local rainfall and tends to be shallower, as opposed to overflow of large rivers onto 620 adjacent floodplains. The four alternative subregional datasets assessed here - three hydrological 621 models (one for Curuai and two for Janauacá) and one classification of ALOS-PALSAR data for 622 the Llanos de Moxos area - were generally better or similar to some of the best-performing basin-623 scale ones, as could be expected given their fine tuning for the specific areas, which often includes 624 local topographic surveys.

Some of the datasets merging multiple data sources overestimated the inundation area of individual wetland complexes the most, especially GIEMS-D15, GIEMS-D3 and GLWD. Furthermore, CIFOR was originally designed for peatland mapping in the tropics, and generally overestimates inundation, suggesting a widespread distribution of wetlands along interfluvial terraces across the whole basin that may include areas of poorly drained soils lacking surface water. For the individual wetland complexes, however, CIFOR generally underestimated inundation and had a poor 631 representation of spatial patterns of inundation (low Fit metric). WAD2M underestimated the 632 maximum inundation the most, which is understandable given its removal of open water areas and 633 because its main inputs (CIFOR and SWAMPS) also underestimated inundated areas as indicated 634 by the subregional validation datasets.

635

636

## 3.2.2 Individual inundation patterns based on SAR data

637 Regarding the maximum inundation extent, the Janauacá case provides a representative 638 example to understand the differences among multiple L-band SAR datasets: these estimated total 639 inundated area as 209 km<sup>2</sup>, 184 km<sup>2</sup> and 446 km<sup>2</sup> for Hess, Chapman and Rosenqvist, respectively, in contrast to 404 km<sup>2</sup> with the subregional ALOS-PALSAR-based dataset (12.5 m resolution; 640 641 Pinel et al., 2019). Part of these differences occur because of interannual variability, but other 642 factors such as spatial resolution and algorithm differences seem relevant. Rosenqvist led to a more 643 consistent estimation of the spatial inundation extent in terms of maximum inundation (Table 3) 644 and inundation spatial patterns (Fit metric; Table S3), which can be a consequence of its higher 645 spatial resolution (50 m) in contrast to the other two (90 m; Figure S3). Overall, Rosenqvist 646 provided the largest inundation extent among SAR datasets across all areas along the Amazon 647 mainstem floodplain, except for the Curuai floodplain and the savanna wetlands, as well as the 648 closest agreement with subregional validation datasets (-9%  $\pm$  13%; average  $\pm$  S.D.). Hess 649 estimated the largest inundation area in the savanna wetlands (Llanos de Moxos, Roraima and 650 Negro). However, Hess' estimate is 39% larger than the subregional validation dataset for Llanos 651 de Moxos, while the other two SAR estimates are lower (-26% and -41% for Chapman and 652 Rosenqvist, respectively).

653 One important question remains about the low-water period, as discussed in the previous section 654 for the basin-scale analysis. Hess suggests much more inundation for this period for the Amazon 655 mainstem floodplains (54,500 km<sup>2</sup>), mainly for the upstream forested reaches, and for the whole 656 basin in general (284,200 km<sup>2</sup>), than recent estimates with ALOS (28,500 and 91,200 km<sup>2</sup>) and 657 ALOS-2 data (19,500 and 42,400 km<sup>2</sup>). An assessment with the subregional datasets along the 658 Amazon floodplain suggests that Hess overestimates the minimum extent for Curuai, Mamirauá 659 and lower Amazon River, and is accurate for the Janauacá floodplain lake. Rosenqvist generally 660 underestimates the minimum inundation. For instance, for the Mamirauá dataset, the minimum 661 extent (i.e., permanently flooded areas) sums up to 715 km<sup>2</sup>, which is increased to 1545 km<sup>2</sup> if 662 considering all pixels flooded for more than 295 days per year. For this area, the SAR estimates 663 are 1756 km<sup>2</sup> (Hess), 866 km<sup>2</sup> (Chapman) and 422 km<sup>2</sup> (Rosenqvist). Overall, this suggests that 664 the actual value of minimum inundation across the central Amazon floodplains is somewhere 665 between the Hess and Rosenqvist estimates.

666

667 3.2.3 Challenges over floodable savannas

668 Large discrepancies are observed for the Roraima and Negro floodable savannas. Roraima 669 wetlands are small river floodplains interspersed with open savannas subject to flooding, which 670 can be identified by optical data. In addition, the typical timing of high and low water in the 671 Roraima region coincides approximately with the JERS-1 dual-season mosaics that were designed 672 to reflect the seasonality of the central Amazon River floodplain (Hamilton et al. 2002). For these 673 reasons, the JERS-1-based dataset by Hess et al. (2015) seems to satisfactorily represent most of 674 the Roraima wetlands. However, it misses some small-scale riparian forests, given its 90 m spatial 675 resolution and snapshot coverage that likely missed flooding events on smaller, flashier rivers

676 (Figure S5). Thus, the maximum inundation is likely higher than the Hess estimate (8,900 km<sup>2</sup>), 677 which in turn is larger than the other ones based on SAR (1,900 - 4,100 km<sup>2</sup>). The only dataset to 678 estimate a higher value is the coarse SWAF-HR (18,100 km<sup>2</sup>), which is similar to the value 679 previously estimated by Hamilton et al. (2002) (16,500 km<sup>2</sup>), also with coarse data (SMMR passive 680 microwave), though a part of the discrepancy may be due to interannual variability. More studies 681 are necessary for this area to understand its actual inundation extent and dynamics. Similarly, the 682 inundation estimates in the Negro interfluvial savannas are subject to large uncertainty, with the 683 long-term maximum inundation varying between 95 (GLWD) and 20,700 km<sup>2</sup> (CIFOR), 684 considering all basin-scale datasets. SAR-based estimates were between 5,900 and 15,800 km<sup>2</sup>. In contrast, for the Pacaya-Samiria interfluvial area, which includes a large complex of forested 685 686 wetlands, peatlands and palm swamps, the discrepancies are smaller than for the savanna 687 interfluvial regions, although still considerable. The basin-scale SAR ranged between 24,000 km<sup>2</sup> 688 (Chapman) and 56,200 km<sup>2</sup> (Rosenqvist), with the subregional validation dataset yielding 57,900 689 km<sup>2</sup>. The good agreement between Rosenqvist and the subregional dataset was already reported 690 by Rosenqvist et al. (2020).

691

Table 3. Long-term maximum inundation areas (km<sup>2</sup>) for the 11 wetland complexes (up to three subregional datasets per complex) and the 18 basin-scale datasets. The subregional values refer to the following datasets, in this order (comma-separated values relate to areas with more than one dataset available): Curuai - ALOS (Arnesen et al., 2013) and LISFLOOD-FP model (Rudorff et al., 2014); Uatumã - ALOS (Resende et al., 2019); Janauacá - ALOS (Pinel et al., 2019), hydrologic model (Bonnet et al., 2017) and TELEMAC-2D model (Pinel et al., 2019); Mamirauá - ALOS (Ferreira-Ferreira et al., 2015); Pacaya-Samiria - ALOS-2 PALSAR-2 (Jensen et al., 2020); Llanos de Moxos - MODIS (Ovando et al., 2016) and ALOS (Ovando et al., 2016); and Lower Amazon River - MODIS (Park et al., 2016)

						Pacaya-	Llanos de	Lower	Amazon		Roraima	Negro
	Dataset	Curuai	Uatumã	Janauacá	Mamirauá	Samiria	Moxos	Amazon	mainstem	Purus	savannas	savannas
	Cubaccional	4162,	1471	404, 336,	4476	57012	125422,	56700				
	Subregional	3720	1471	176	4470	57915	133470	50722	-	-	-	-
Multiple	GIEMS-2	3080	984	623	3344	23344	156176	79871	116379	7208	7173	12237
datasets	SWAMPS	3359	722	280	1131	9929	88753	58626	72468	5618	4970	8819
at coarse												
resolutio	WAD2M	681	243	166	888	42635	102780	29276	49261	6698	3173	15450
n												
Multiple	GIEMS-D3	4643	2732	505	3569	11562	150285	92908	127552	9045	12355	15123
datasets	CIFOR	3796	994	177	1714	52590	116201	43509	86301	10844	3728	20712
at high	ESA-CCI	3236	855	260	3045	28727	39795	37475	84803	8883	510	12623
resolutio	GIEMS-D15	4635	2681	416	2444	44536	117979	86123	127150	11186	8129	14854
n	GLWD	4275	2267	535	4259	79124	40661	67746	140921	14840	1048	95
	SWAF-HR	4439	2199	388	3205	16900	159712	69539	110468	10785	18146	15375
Hydrolo	THMB	2883	554	164	2840	27748	52693	39193	89658	19733	4307	3640
gical	CaMa-Flood	4246	1613	534	3208	34096	80725	63963	118577	20947	3454	6560
model	MGB	4098	1549	474	3750	33344	21757	61997	115047	20394	240	3224
Optical	G3WBM	2732	628	135	795	2694	9564	27451	37718	2351	352	1238
sensors	GLAD	3479	832	204	1141	4196	38897	36930	53121	3903	3495	3885
	GSWO	3163	675	150	962	3637	19240	31191	44731	2982	1442	1880
Syntheti	Chapman	2796	934	184	2694	24001	73710	39677	77632	12499	4077	5935
с	Hess	3996	1045	209	3985	39741	174198	52156	115822	15155	8950	15758
Aperture	Rosenqvist	3055	1238	446	4362	56160	92693	55262	126806	20738	1867	9935
Radar	1.00											
	Average	3477	1264	325	2630	29720	85323	54050	94134	11323	4856	9297
	S.D.	949	748	163	1226	20591	52387	19956	32503	6185	4666	6201
	CV	27%	59%	50%	47%	69%	61%	37%	35%	55%	96%	67%

# 699 2019). Average, standard deviation (S.D.) and coefficient of variation (CV) are presented for each area in the last

700 rows.

701

# 702 **3.3** How much do the datasets agree on the spatial distribution of inundation?

Agreement maps of the high resolution datasets ( $\leq 1$  km spatial resolution) were developed for both long-term maximum (14 datasets available) and minimum inundation areas (10 datasets), based on the number of inundation datasets coinciding over a 1 km pixel (Figures 7 and 8 and their categorization for specific regions in Figure 9). Overall, 31% of the Amazon lowlands area (i.e., 1.59 x  $10^{6}$  km<sup>2</sup> out of 5.11 x  $10^{6}$  km<sup>2</sup>) has been estimated as subject to inundation by at least one dataset (bottom left panel, Figure 7). Based on the agreement between two datasets, this value decreases to 948,300 km<sup>2</sup>, which is larger than the value estimated when there is agreement among four datasets (553,200 km<sup>2</sup>). This latter estimate is more similar to the average maximum inundation as estimated by the ensemble of datasets (559,300 km<sup>2</sup>) and the three SAR-based ones (599,700 km<sup>2</sup>). Furthermore, there is a lower agreement for the minimum inundation than for the maximum inundation among individual regions (Figure 9).

714 For specific regions, a high degree of agreement for floodplains dominated by open water areas is 715 evident for the lower Amazon River reaches, followed by the forested floodplains fringing large 716 rivers, especially along the Amazon mainstem, Purus and Negro rivers. The generally higher 717 accuracies over central Amazon floodplains may also be related to the attention that dataset 718 developers have devoted to it, in contrast to other regions. Furthermore, the maximum floodplain 719 extent can be somewhat delineated with terrain elevation data (i.e., DEMs) using algorithms such 720 as HAND (Rennó et al., 2008), which helps to explain the relatively small disagreement for 721 floodplains fringing the largest rivers, and is particularly effective with vegetation bias-removed 722 DEMs (O'Loughlin et al., 2016; Yamazaki et al., 2017). The best agreement (for both maximum 723 and minimum inundation extent) occurred over the Curuai floodplain along the lower Amazon 724 mainstem, with 37% of its area being estimated as subject to inundation by all 14 datasets (Figure 725 9a). An agreement among all 14 datasets occurred, in part (i.e., more than 10% of the wetland 726 area), for the central Amazon floodplains (Curuai, Uatumã, Janauacá and lower Amazon River) 727 because of their relatively large fractions of open water areas.

In the interfluvial wetlands (Negro and Roraima savannas, Pacaya-Samiria and Llanos de Moxos),
the inundation patterns are less dependent on riverine overflow and more dependent on local

730 rainfall, making them less predictable (Hess et al., 2003). The disagreement for both maximum 731 and minimum inundation area is the largest across all regions, e.g., 65–78% of their flooded areas 732 were mapped by only one model for the minimum inundation (Figure 9b). The Llanos de Moxos 733 is conspicuous as a region of particular disagreement, perhaps because flooding is mainly shallow 734 and in vegetated areas (mainly savannas/grasslands), and is highly variable from year to year. In 735 general, the smaller the flooded patches the higher the challenge to map them, not only because of 736 resolution but also due to small-scale variation in topography. Similar disagreement occurred in 737 other interfluvial wetlands such as the Negro and Roraima savannas, and would be expected 738 elsewhere in savanna floodplains of South America (e.g., Pantanal, Llanos de Orinoco and Bananal Island; Hamilton et al., 2002). The poor agreement over interfluvial areas, however, may also 739 740 partly reflect the longer history of study of Amazon mainstem floodplains, for which there are 741 river gage records that reflect floodplain water levels and inundation, while more remote areas 742 such as the Negro savannas and Pacaya-Samiria regions are more challenging to represent with a 743 few gages, and have received less attention. The challenges in estimating inundation over 744 interfluvial areas also affect the SAR-based datasets, which disagreed the most over these regions 745 (see section 3.5 and discussion in Rosenqvist et al., 2020).



Figure 7. Agreement for maximum inundation area among 14 basin-scale datasets at high resolution (≤1 km spatial
resolution): G3WBM, ESA-CCI, GLAD, GSWO, GLWD, CIFOR, GIEMS-D15, GIEMS-D3, Chapman, Hess,
Rosenqvist, SWAF-HR, CaMa-Flood and MGB. A given pixel of a dataset with resolution higher than 1 km that had
more than 50% of flooding at the maximum inundation extent is classified as inundated.



Figure 8. Agreement for minimum inundation area among 10 basin-scale datasets at high resolution (≤1 km spatial
resolution): GIEMS-D15, Chapman, Hess, Rosenqvist, SWAF-HR, CaMa-Flood, MGB, GIEMS-D3, GSWO and
GLAD. A given pixel of a dataset with resolution higher than 1 km that had more than 50% of flooding at the minimum
inundation extent is classified as inundated.



Figure 9. Degree of agreement for (a) maximum and (b) minimum inundation area for 10 individual wetland complexes, based on the 1 km agreement map (Figures 7 and 8). The percentage values indicate the fraction of each area where a given number of datasets agreed that it was flooded, e.g., 14 models agreed that 37% of the Curuai area was flooded in the maximum inundation extent. The class with number 1 indicates the fraction of the area that only one dataset estimated as being inundated. The class "others" refers to all classes that had less than 5% of pixels estimated as being inundated.

### 769 **3.4 Quantifying the inundation extent of different wetland types**

Amazon wetlands include a myriad of ecosystems varying in geomorphology, hydrology, and vegetation cover. The classification system proposed by Junk et al. (2011) differentiated Amazon wetlands according to amplitude and range of water level change. Wetland types ranged from the forested swamps with stable water levels to river floodplains with oscillating water levels, and to interfluvial areas with small seasonal water level amplitude due to the main contribution of local rainfall and runoff (Fleischmann et al., 2020; Junk et al., 2011; Ovando et al., 2018).

776 A simpler yet hydrologically meaningful classification is the categorization into river floodplains 777 and interfluvial wetlands adopted here, since the former typically have a greater hydrological 778 connection to the main river and thus are subject to a different control of inundation area by river 779 levels (Reis et al., 2019a). We performed a quantitative analysis of the inundation area in these 780 two main hydrological classes. All pixels considered flooded by at least two datasets, based on the 781 1 km agreement map for maximum inundation extent (Figure 7), are presented in Figure 10. 782 Overall, the medium to large river floodplains (upstream drainage area > 1000 km<sup>2</sup>) have a larger 783 inundation extent than the category with small floodplains and interfluvial areas. An average total 784 area subject to inundation of  $317,800 \pm 84,400 \text{ km}^2$  (average  $\pm$  S.D.; median equal to  $323,700 \text{ km}^2$ ) 785 was obtained for the medium to large floodplains, not including the optical and land cover datasets 786 (G3WBM, GLAD, GSWO and ESA-CCI). A greater area for large floodplains was estimated by 787 all except for CIFOR, SWAMPS and WAD2M. Two datasets estimated a similar value between 788 the two classes (Chapman and GIEMS-2), which may be related to an overestimation of basin-789 scale isolated flooded patches.

Large floodplains fringing the main rivers, especially along the Amazon River, have been largely
addressed by previous studies (Table 1 and Table S1). However, large river floodplains are also
present in less studied reaches, e.g., in the upper Napo and Içá rivers in northwest Amazon basin,

and upper Xingu in the southeastern portion (see location in Figure 1). These upper reaches are subject to more sporadic, flashy river hydrological regimes (Hamilton et al., 2007), which make their inundation area difficult to map with current datasets of relatively low temporal resolution. In our analysis, the non-floodplain areas include mainly the large interfluvial areas (black rectangles in Figure 10), small river floodplains that are challenging to detect with currently available datasets, and some reservoirs, such as Balbina reservoir on the Uatumã River.

799 Besides the central Amazon floodplains, which have been widely studied, other wetland 800 complexes require more attention, such as the Negro and Roraima savannas; the latter was only 801 assessed by a single study to our knowledge (Hamilton et al., 2002). The inundation mapping of 802 the Pacaya-Samiria region in the upper Amazon has received scientific attention recently (Jensen 803 et al., 2018; Rodriguez-Alvarez et al., 2019), partially because of the region's role as a carbon sink 804 via formation of peat (Draper et al., 2014; Lähteenoja et al., 2012). Regarding open water areas, 805 Melack (2016) reported values ranging from 64,800 km<sup>2</sup> (Melack and Hess, 2010) to 72,000 km<sup>2</sup> 806 (SRTM Water Body Data) and 92,000 km<sup>2</sup> (Hansen et al., 2013) for the Amazon basin (< 500 m 807 in elevation). The three Landsat-based datasets assessed here, which are mainly capable of 808 detecting open water areas, estimate 98,500 km<sup>2</sup> (G3WBM), 128,500 km (GSWO) and 187,600 809 km<sup>2</sup> (GLAD).



Figure 10. Quantification of maximum inundated areas over river floodplains with drainage area larger than 1,000 km<sup>2</sup>, and interfluvial wetlands and small floodplains (area < 1,000 km<sup>2</sup>) within the Amazon basin. The maximum inundation map depicts all 1 km pixels with at least two datasets agreeing (i.e., a reclassification of Fig. 7), in order to avoid overestimation caused by pixels with only one dataset classifying them as subject to inundation. The four large areas of interfluvial wetlands are highlighted with black rectangles (Pacaya-Samiria, Llanos de Moxos, Negro and Roraima savannas).

## 819 **3.5** Limitations in comparing the inundation area datasets

Some of the differences in large-scale inundation mapping highlighted by our comparison occur because distinct datasets map temporal variation in inundation in different ways, varying for example in sensor type, post processing, and spatial resolution. Figure 11 shows the agreement maps for maximum inundation for four classes of datasets, considering the 14 basin-scale highresolution datasets. Those based on multiple datasets (GLWD, CIFOR, GIEMS-D3, GIEMS-D15,
SWAF-HR) have the best agreement for the Llanos de Moxos area, and to a smaller degree, for
Pacaya-Samiria, Negro and Roraima wetlands. The L-band SAR datasets have less overall
agreement (Figure 11c), while the optical data are mainly applicable to open water areas in the
Amazon mainstem floodplain (Figure 11b). The 1D hydrological models cannot represent
interfluvial wetlands where flooding is not controlled by river level and discharge (Figure 11d).



Figure 11. Amazon basin (< 500 m elevation) agreement maps at 1 km resolution, for maximum inundation and for</li>
each type of dataset, considering only the high-resolution datasets (≤ 1 km spatial resolution): (a) six datasets based
on merging of multiple datasets (GLWD, CIFOR, GIEMS-D3, GIEMS-D15, SWAF-HR, ESA-CCI), (b) three datasets
based on optical sensors (G3WBM, GLAD, GSWO), (c) three datasets based on synthetic aperture radar (Hess,
Chapman, Rosenqvist), and (d) two hydrological models (MGB and CaMa-Flood). The right column graphs present
the total inundation area in the Amazon basin for a given number of datasets agreeing, e.g., the basin area where the
two hydrological models (Fig. d) agree to be flooded is 390,900 km<sup>2</sup>.

839 The different methodologies used to produce each dataset complicate their direct comparison 840 (Rosenqvist et al., 2020), and some methodological differences produce systematic differences and 841 bias among the data sources included in our comparison. Here we used datasets covering long-842 term dynamics (e.g., GIEMS or hydrologic models), short-term dual-season (e.g., Rosenqvist, 843 spanning four years), and a particular year (e.g., Hess). Some datasets use alternative approaches 844 to derive long-term maximum inundation area, such as GIEMS-D15, which generated estimates 845 by merging 3-year moving-window maximum values of GIEMS with the GLWD dataset. 846 Therefore, a comparison of all these datasets must be performed with consideration of their 847 methodology. For instance, the comparison of dual-season datasets against monthly datasets can 848 yield erroneous conclusions, although it has been a common practice to directly compare such 849 datasets. Some datasets also consider a "high-water assumption" (Ferreira-Ferreira et al., 2015; 850 Hess et al., 2003), whereby the high-water maps are forced to contain all flooded pixels from the 851 low-water map.

852 In addition to methodological differences, each dataset was developed for different periods (Table 853 1), and thus interannual and seasonal variability accounts for some of the differences among them. 854 To address this, we performed an annual analysis (Figure 5), which suggests that the long-term 855 inundation estimate is fairly stable for each dataset despite some interannual differences. In fact, 856 the temporal variability of each dataset is generally smaller than the differences in comparison 857 with the other estimates. However, the Amazon hydrological cycle has been shifting over decades 858 (Barichivich et al., 2018; Gloor et al., 2013), and a recent increase in maximum water levels in the 859 central Amazon suggests a new hydroclimatic state (Espinoza et al., 2019). Some wetlands have 860 also been subject to forest loss, and so the detectability of inundation by remote sensing may have 861 increased over time, e.g., major deforestation has occurred along the lower Amazon River floodplain (Renó et al., 2011). Similarly, widespread burning might be converting black-water floodplain forests into savanna vegetation (Flores and Holmgren, 2021). In addition, in some regions, such as the southern Amazon, an increase in the dry-season length has been observed, which is a major climatic constraint for forest sustainability (Fu et al. 2013; Staver et al., 2011). However, analyzing long-term change in inundation patterns is beyond the scope of this study, and thus we assumed stationarity in our comparison framework.

868 Another important challenge is to find a common definition of wetlands among datasets. Here we 869 focused on inundation extent, however some datasets (e.g., CIFOR) represent peatland locations 870 instead of inundated areas, although their areas of peat formation often include inundated areas. 871 Estimates based on SAR or passive microwave emission may also be sensitive to saturated soil 872 without standing water above it, and thus the observed inundation estimates can have some 873 ambiguity. Hydrologic models provide simulated surface water extent, and we mapped inundation 874 accounting for pixels with water depth greater than zero. While hydrologic models have 875 uncertainties related to model structure (e.g., inadequate representation of inundation processes), 876 input data (e.g., DEM and climate forcing) and parameterization (e.g., soil water capacity and river 877 channel width and depth; assumptions of level water surfaces between rivers and their floodplains), 878 remote sensing-based datasets have uncertainties related to spatial and temporal resolutions (e.g., 879 coarse spatial resolution not capable of detecting small patches), and detection uncertainty (e.g., 880 dense vegetation canopies can obscure passive microwave emission from underlying surfaces). 881 Thus, a comparative framework provides an opportunity to highlight and stress the uncertainties 882 and limitations of each dataset.

Hydrologic models currently available at the Amazon basin scale are one-dimensional, and thusare capable of simulating flooding mainly along river floodplains, as corroborated by various

885 validation exercises in the Amazon that have relied on the Hess, GIEMS and SWAF-HR datasets 886 (Fleischmann et al., 2020; Luo et al., 2017; Paiva et al., 2013; Zhou et al., 2021). These models 887 are also largely dependent upon accurate DEMs, which are still challenging to obtain over tropical 888 forested floodplains. Furthermore, given that a 500 m elevation mask (Amazon lowlands) has been 889 used for some SAR datasets (Hess et al., 2015), and the difficulty of some radar and passive 890 microwave ones to detect inundation at high elevations due to slope and snow effects, for instance 891 (Parrens et al., 2017), we have adopted the same 500 m threshold in our lowland mask to improve 892 the comparability among datasets. However, even though higher elevation wetlands amount to 893 much less total area compared to lowland wetlands, understanding their flooding dynamics is 894 important for some parts of the Amazon basin. Although some datasets, especially the hydrological 895 models (MGB, CaMa-Flood and THMB), are capable of estimating inundation in higher elevation 896 parts of the basin, in this case uncertainties may also be large given errors in precipitation (low 897 density of in situ gauges and high rainfall spatial heterogeneity) and thus runoff fields over 898 mountainous areas, as well as the tendency for river flows to vary over short time scales (Espinoza 899 Villar et al., 2009; Zubieta et al., 2015). Furthermore, the availability of in situ river discharge 900 measurements for model calibration and validation is lower in the Andean Amazon (Feng et al., 901 2020; Wongchuig et al., 2019; Zubieta et al., 2017).

902 Our analyses were performed at 1 km resolution and at regional scales, which avoids geolocation 903 problems that affect analyses at higher resolutions (e.g., 30 or 90 m). Small disagreements among 904 our estimates and the values presented in the original publications may also arise from the use of 905 the WGS84 datum with a geographical coordinate system for all datasets (except for SWAMPS 906 which was provided in the EASE-Grid format). Also, the coarse-resolution datasets, especially 907 GIEMS-2 and SWAMPS with 25 km spatial resolution, can be difficult to compare with estimates 908 for individual wetland complexes (e.g., Curuai and Janauacá), since only a few 25-km pixels may
909 be located within the wetland boundaries.

910 The quantification of inundation over larger river floodplains (Figure 10) is also subject to 911 uncertainties. The maximum floodplain lateral extent was estimated based on an automatic buffer 912 procedure around the Hydrosheds drainage network, further manually edited by considering the 913 three SAR-based, basin-scale datasets and the MERIT DEM-based topography. Although it 914 captures the basin-scale geomorphological differences along major floodplains, some uncertainties 915 remain regarding the true lateral extent for areas where rain-fed savanna floodplains are present 916 (e.g., Llanos de Moxos, Roraima), and where flooding extend far from the main rivers (e.g., 917 Pacaya-Samiria). For these areas in particular, we assumed buffer values similar to adjacent 918 upstream and downstream floodplains (e.g., the Amazon River downstream of Pacaya-Samiria), 919 which is reasonable but should undergo future scrutiny, including local ground-based surveys.

920

### 921 4. Perspectives and recommendations

922 Considerable advances have been achieved in recent decades in the mapping of inundation extent 923 across the Amazon basin. Here, we have presented an analysis of 29 inundation datasets for the 924 basin, covering multiple scales, spatial and temporal resolutions, and data sources. We showed 925 that large discrepancies persist, and this is especially true at local scales. Below we present some 926 perspectives and recommendations for future development of inundation mapping in the world's 927 largest river basin.

# 929 4.1 Which are the most reliable data sources for inundation mapping in the Amazon River 930 basin?

931 At basin scale, the Rosenqvist ALOS-2 PALSAR-2 dataset is available at 50 m, and shows a good 932 overall agreement with the 90 m Hess one over the large river floodplains, while the latter seems 933 more accurate for interfluvial savanna floodplains (e.g., Negro and Roraima). The high agreement 934 is observed mainly for the maximum inundation estimates, while for the minimum inundation area, 935 important disagreements persist and more studies should be performed to understand them. 936 Overall, the Hess' dataset has been the Amazon inundation benchmark for many years, and still 937 provides satisfactory estimates. Detection of inundation by L-band SAR has a sound theoretical 938 and empirical basis that has been validated for the Amazon (Rosenqvist et al., 2002; Hess et al., 939 2003). Optical datasets with resolution higher than 30 m are available, but detection of inundation 940 is restricted to non-vegetated wetlands and clear-sky periods, and is most applicable in the lower 941 Amazon River floodplains. ALOS-PALSAR at 12.5 m resolution and Sentinel SAR at 10 m 942 resolution (with C-band and limited vegetation penetration) can be applied to specific regions. 943 Time series of these datasets can estimate seasonal variations in inundation, but are limited by the 944 length of the acquisitions. Weekly to monthly, spatially coarser data (25 km) are available from 945 passive microwave-based datasets such as GIEMS, SWAF and SWAMPS. Downscaling 946 techniques have improved their spatial resolution to 90 m (GIEMS-D3) and 1 km (SWAF-HR). 947 Hydrological models (e.g., CaMa-Flood and MGB) are capable of accurately estimating 948 inundation over river floodplains, and at high temporal resolution depending on the input rainfall 949 data (e.g., hourly to daily). However, they are still limited over interfluvial wetlands with less

connection with rivers, unless they are upgraded for simulating 2D inundation processes and
complex floodplain flow paths (Fleischmann et al., 2020; Yamazaki et al., 2014).

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# 953 4.2 What are the current capabilities of flood frequency mapping?

954 At the basin scale, high-resolution, long-term average flood frequency can be estimated by four of the datasets analyzed here (GIEMS-D3, SWAF-HR, MGB and CaMa-Flood), with spatial 955 956 resolutions ranging from 90 m to 1 km. Although multiple SAR data are currently available (e.g., 957 Sentinel-1, ALOS-PALSAR and ALOS-2 PALSAR-2), they have a limited temporal resolution, 958 and we still do not have a flood frequency dataset of higher spatial resolution (i.e., better than 90 959 m) for the whole basin based on SAR. The discrepancies among the available datasets are notable 960 (Figure 12). The average of the basin-scale flood frequency shows a higher agreement for areas 961 with high flood frequency along the lower Amazon River (Figure 12a). These are associated with 962 a high proportion of open water areas, and have lower uncertainty (Figure 12b). Generally, there 963 is a smaller variation along floodplains bordering the major rivers (except for their fringes) than in 964 interfluvial areas, especially in the Negro and Roraima wetlands (Figure 12b). Detailed inundation 965 mapping for the Mamirauá Sustainable Development Reserve in the Amazon mainstem floodplain 966 (Figure 12c) reinforces the challenges for mapping local spatio-temporal inundation dynamics. 967 The northern part of the Mamirauá reserve has a shorter flood frequency in all datasets, while three 968 of them (SWAF-HR, GIEMS-D3, CaMa-Flood) estimate that large portions are never flooded. For 969 the southern part, there is some convergence for areas that are frequently flooded.



972 Figure 12. Analysis of flood frequency for (a) basin-scale average and (b) coefficient of variation of the long-term
973 flood frequency estimated from four high-resolution dynamic datasets (GIEMS-D3, SWAF-HR, CaMa-Flood and
974 MGB). (c) The four basin-scale datasets are compared to a subregional validation dataset (i.e., the ALOS-PALSAR975 based classification by Ferreira-Ferreira et al. (2015), displayed in the top left panel) for the Mamirauá Sustainable
976 Development Reserve along the central Amazon River mainstem (location shown by black outline in figure a).

#### 978 4.3 Implications for biogeochemistry, ecology and flood management

979 The divergent estimates of Amazon inundation extent have major implications for the 980 quantification of the role of wetlands in global biogeochemical cycles, ecosystem processes and 981 natural disaster management.

982 First, different datasets have been used to quantify the role of Amazon wetlands in the carbon cycle 983 (Guilhen et al., 2020; Melack et al., 2004; Richey et al., 2002; Saunois et al., 2020). An 984 intercomparison assessment of global models forced with different inundation datasets for the 985 Amazon could provide insights into their sensitivity to the estimated inundation. This would be 986 particularly important for modeled estimates of methane flux, given the region's significant 987 contribution to global methane emissions from natural wetlands (Basso et al., 2021). Furthermore, 988 for a proper estimation of methane and carbon dioxide fluxes, dynamic inundation estimates are 989 necessary; this study shows that most coarse-resolution dynamic datasets capture relatively well 990 the seasonality (i.e., the timing of high and low water periods) of annual flooding at a large scale 991 (but not at the local scales), but the magnitude of inundation area over time is still associated with 992 significant errors (Fig. S6).

The understanding of the ecology of Amazon freshwaters has benefited from advances in remote sensing-based mapping of inundation. Hydrological variables of interest in relation to wildlife (Alvarenga et al., 2018; Bodmer et al., 2018) and vegetation distribution (Hess et al., 2015, 2003) include hydroperiod, floodplain water depth (Arantes et al., 2013; Fassoni-Andrade et al., 2020), and (lateral) surface water connectivity (Castello, 2008; Duponchelle et al., 2021; Reis et al., 2019a, 2019b), and should be better estimated by future datasets. In addition, many wetland ecosystem studies are performed at the tree stand level (e.g., floristic inventories) and require high

1000 spatial resolution inundation estimates to perform meaningful spatial analyses accounting for 1001 spatial heterogeneity of wetland vegetation. Furthermore, besides a simple interfluvial/floodplain 1002 categorization of wetlands as performed here (section 3.4), which is reasonable from a hydrologic 1003 perspective, improving our understanding of the ecology of Amazon freshwater systems requires accurate mapping of habitats and their diverse vegetation types (e.g., grasslands, particular 1004 1005 monodominant tree species, herbaceous plants). For instance, floodplain forest cover has been 1006 positively correlated to fishery yields (Arantes et al., 2018) and fish abundance (Lobón-Cerviá et 1007 al., 2015). While this wetland habitat mapping has already been done by some initiatives at the 1008 basin (Hess et al., 2015, 2003) and subregional scales (Ferreira-Ferreira et al., 2015; Silva et al., 1009 2013), there is still a need for higher resolution and dynamic datasets.

1010 Regarding flood monitoring in the context of natural hazard management, the flood warning 1011 systems of regional water authorities in the basin provide information based on river discharge and water level at monitoring stations (e.g., Brazil's Geological Survey SACE system; 1012 1013 <http://sace.cprm.gov.br/amazonas/#>). In addition, there are other available monitoring and 1014 forecasting services that have been developed for the global scale, such as the Global Flood 1015 Detection System (https://www.gdacs.org/flooddetection/), based on remote sensing, and the Global Flood Monitoring System (http://flood.umd.edu/) and the Global Flood Awareness System 1016 1017 (https://www.globalfloods.eu/), based on hydrological modeling. The currently available, basin-1018 scale inundation datasets are unable to map flood hazard at the detailed resolution required for 1019 flood management applications, especially concerning urban areas (Almeida et al., 2018). High-1020 resolution flood mapping has been achieved using hydraulic modeling based on local surveys of 1021 river bathymetry and floodplain LiDAR DTM, but only for a few specific sites such as the lower 1022 Madeira River (Fleischmann et al., 2021).

### 1024 4.4 Future opportunities and recommendations

1025 Future satellite missions will provide opportunities for improved inundation mapping in the 1026 Amazon, especially the polarimetric and interferometric L-band SAR data from the upcoming 1027 NASA/ISRO mission (NISAR), the P-Band BIOMASS mission from ESA, and the Ka-band Radar 1028 Interferometer (KaRIn) swath observations from the forthcoming SWOT mission (Biancamaria et 1029 al., 2016). New inundation detection technology under development with Global Navigation 1030 Satellite System-Reflectometry (GNSS-R), such as the Cyclone GNSS (CYGNSS) constellation 1031 of GNSS-R satellites, holds promise to provide higher frequency observations of water level 1032 changes (Jensen et al., 2018; Ruf et al., 2018; Rodriguez-Alvarez et al., 2019). Further studies with the ALOS-2 PALSAR-2 data also are promising, in order to achieve new dynamic inundation 1033 1034 detection, as well as ongoing assessments of the accuracy of the newly available high temporal 1035 resolution inundation datasets (e.g., SWAF-HR with 3-day availability). Consistent and updated 1036 validation products of Amazon inundation are required, which could be derived from airborne, 1037 satellite, or UAV-based LiDAR surveys along multiple wetlands, in particular for overlooked 1038 wetlands such as the Negro and Roraima floodable savannas where measured water levels in rivers 1039 may not adequately predict inundation area. This is especially important for the minimum 1040 inundation extent, which showed large uncertainties among the multiple datasets.

1041 Comprehensive comparisons among multiple inundation datasets are scarce in the literature, yet 1042 are valuable ways to understand benefits and limitations of each of them. A few examples include 1043 a continental-scale assessment of flood model hazard maps in Africa (Trigg et al., 2016) and 1044 regional assessment of inundation in floodplains of Nigeria and Mozambique (Bernhofen et al., 1045 2018), both based on global hydrological models. Similar initiatives for other areas worldwide 1046 would be welcome, especially for those that lack consistent flood mapping, such as the Congo and 1047 other large wetland systems in Africa (Papa et al., 2022). Furthermore, the combination and 1048 integration of multiple inundation datasets present a promising and effective approach (Gumbricht 1049 et al., 2017; Hu et al., 2017). We recommend that future developments include optimal data 1050 merging approaches, e.g., by integrating inundation extent into models accounting for water cycle 1051 components with multiple constraints (Meyer Oliveira et al, 2020; Pellet et al., 2021), and by 1052 considering new types of datasets (e.g., GNSS-R; Jensen et al., 2018). Bias of different datasets 1053 could be corrected based on intercomparisons such as those we present here. For instance, recent 1054 studies have performed inundation bias correction using the Hess dataset (Aires et al., 2013; 1055 Sorribas et al., 2016). However, merging of different datasets must be performed with caution, in 1056 a consistent way, avoiding double counting of surfaces, as well as missing others: its success 1057 critically depends upon a good understanding of the limitations and assets of each individual dataset. The optimal combination of hydrological-hydraulic models with satellite flood maps using 1058 1059 techniques such as data assimilation is also a promising alternative at the basin scale (Wongchuig 1060 et al., 2020).

1061 There is a need for the development of more large-scale 2D hydrological model applications, 1062 especially for large wetland complexes such as the Llanos de Moxos and Pacaya-Samiria, to better 1063 represent inundation dynamics (Fleischmann et al., 2020). 2D models have been applied mainly 1064 to some local-scale areas in the Amazon mainstem floodplain (Pinel et al., 2019; Rudorff et al., 1065 2014; Trigg et al., 2009; Wilson et al., 2007). Furthermore, inundation anomalies are still poorly 1066 understood owing to the lack of ground-based inundation observations during extreme floods and 1067 droughts. Therefore, validation of estimates for extreme years has usually been performed with 1068 river water level data (in situ or from satellite altimetry) (Silva et al., 2018; Wongchuig et al.,

1069 2019). Future works should address which datasets and methodologies are the most suitable for 1070 mapping extreme events. Furthermore, besides inundation extent, flood storage (Frappart et al., 1071 2005; Papa et al., 2008; Schumann et al., 2016; Papa and Frappart, 2021) and water velocity (Pinel 1072 et al., 2019) are necessary hydraulic variables to properly address multiple environmental studies 1073 (e.g., flood monitoring, flood attenuation by floodplains, fish floodplain habitats), but to date have 1074 not been well studied in the Amazon.

1075 Finally, there is a need for better-informed usage of the currently available inundation datasets by 1076 multiple local and regional stakeholders (e.g., local water authorities, national water agencies), as 1077 well as research communities not close to remote sensing groups. This will only be achieved 1078 through a two-way interaction with these actors and development of easy-to-access visualization 1079 platforms (i.e., investment in hydroinformatics), as well as training of regional/local user 1080 communities. To this end, we have developed a WebGIS platform (https://amazon-1081 inundation.herokuapp.com/) to display and provide data acquisition links for the inundation 1082 datasets assessed here, which will be continuously updated once new datasets are made available. 1083 The interaction with local users would bring important feedback on the large-scale datasets as well, 1084 for instance through citizen science initiatives that are ongoing in the Amazon 1085 (https://www.amazoniacienciaciudadana.org/).

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1088 Acknowledgments

The authors thank Dr. Fernando Jaramillo, Dr. David Kaplan, Dr. David Marques and Dr. Naziano
Filizola for fruitful comments in an earlier version of this manuscript. The work was part of the
SABERES project financed by the BNPParibas Foundation as part of its "Climate & Biodiversity

1092 Initiative" program 2019. A.S.F. was supported by CNPq (Conselho Nacional de Desenvolvimento 1093 Científico e Tecnológico, Brazil) [grant number 141161/2017-5]. F.P., J.F.F., M.P.B. and F.A. 1094 received support from CNES (SWOT-ST project SWOT for SOUTH AMERICA, ID: 6018-1095 4500066497). F.P. and M.P.B. also received support from CNES (SWOT-ST project SWOT 1096 Wetlands Hydrology Monitoring). F.P. is supported by the IRD Groupement De Recherche 1097 International (GDRI) SCaHyLab. J.M.M. received support from NASA IDS grant NNX17AK49G 1098 and the US National Science Foundation (Division of Environmental Biology, grant 1753856). 1099 E.P. acknowledges Nanyang Technological University (SUG-NAP EP3/19) and Ministry of 1100 Education of Singapore (AcRF Tier1 RT 06/19 and AcRF Tier2 RT 11/21). A.F.R. acknowledges 1101 the Research Foundation of São Paulo (FAPESP, grant #2019/24049-5). S.W. has been supported 1102 by the French AMANECER-MOPGA project funded by ANR and IRD (ref. ANR-18-MPGA-1103 0008). M.C. received funding from NASA IDS grant NNX17AK49G. The SWAF dataset 1104 development was financed by the CATDS and the SWOT-AVAL programs by CNES.

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1733	21-3543-2017
1734	Zubieta, R., Saavedra, M., Espinoza, J.C., Ronchail, J., Sulca, J., Drapeau, G., Martin-Vide, J.,
1735	2019. Assessing precipitation concentration in the Amazon basin from different satellite-
1736	based data sets. Int. J. Climatol. 39, 3171-3187. https://doi.org/10.1002/joc.6009

1742 Supplementary Material

Table S1. List of additional studies that mapped inundation in the Amazon, which were notincluded in the article analysis because of redundancy with the used datasets, or data unavailability.

	Reference	Dataset name / Type	Spatial.	Temporal	Time	Region	Type of
			resolutio	resolutio	period		inundation
			n	n			captured
1	Aires et al.	GIEMS + downscaling	500 m	Monthly	1993-	Central Amazon	All
	(2013)	with SAR			2007		
2	Belger et al.	Radarsat-1 / C-band SAR	25 m	Irregular	2004-	Cuini and Itu (Negro	All
	(2011)				2005	basin)	
3	Bonnet et	Hydrological model		Daily	1997-	Curuai	All
	al. (2008)				2003		
4	Canisius et	Radarsat-2 / C-band SAR	2.5-2.6 m	Irregular	2014-	Lower Amazon river	All
	al., 2019)				2016		
5	Fleischman	MGB / Hydrological-	4 km	Daily	1999-	Negro River basin	All
	n et al.	hydraulic model			2015		
	(2020)						
6	Frappart et	JERS-1 / L-band SAR	90 m	Static	1995-	Negro River basin	All
	al. (2005)			(high and	1996		
				low			
				water)			

7	Getirana et	HYMAP / Hydrological		Daily	1986-	Negro River basin	All
	al. (2012)	model			2006		
8	Guimbertea	ORCHIDEE /	0.5	Daily	1980–	Basin	All
	u et al.	Hydrological model	degrees		2000		
	(2012)						
9	Hawes et al.	ALOS-PALSAR / L-				Juruá floodplain	All
	(2012)	hand SAR	100 m	Irregular	2006-		
					2009		
10	Hoch et al.	PCR-GLOBWB /	30 arcmin	Daily	1985-	Central Amazon	All
	(2017)	Hydraulic model			1990		
11	Langerwisc	LPJmL / Hydrological	0.5	Monthly	1961-	Basin	All
	h et al.	model	degrees		1990		
	(2013)						
12	Lauerwald	ORCHIDEE-	0.5	Daily	1980–	Basin	All
	et al. (2017)	ORCHILEAK / Land	degrees		2000		
		surface model					
13	Lesack and	In situ data	-	-	-	Lake Calado	All
	Melack						
	(1995)						
14	Li et al.	Landsat (Mapbiomas)	30 m	Annual	1985-	Madeira river close to	All
	(2020)				2019	Santo Antônio and	
						Jirau dams	
15	Luo et al.	MOSART / Hydraulic	-	-	-	Basin	All
	(2017)	model					
16	Martinez	JERS-1 / SAR	25 m	Irregular	1993-	Curuai	All
	and Le			(21	1997		
	Toan			images)			
	(2007)						
17	Miguez-	LEAF-Hydro-Flood /	~2 km	Daily	2000-	Basin	All
	Macho and	Hydrological-hydraulic			2010		
	Fan (2012)	model					

18	Meyer	ALOS-PALSAR / L-	100 m	Irregular	2006-	Purus River basin	All
	Oliveira et	band SAR			2010		
	al. (2020)						
10			250	G	2002		<b>F1 11</b>
19	Nardi et al.	GFPLAIN250m /	250 m	Static	2002	Basin	Floodplain
	(2019)	geomorphic approach			(SRTM		S
					mission)		
20	Paiva et al.	MGB / Hydrological-	500 m	Daily	1998-	Basin	All
	(2013)	hydraulic model			2010		
21	Ringeval et	TOPMODEL - LSM /	1 degree	Monthly	1993–	Basin	All
	al. (2012)	Hydrological model			2004		
22	Ringeval et	PCR-GLOBWB /	0.5	Daily	1979 -	Basin	All
	al. (2014)	Hydrological model	degrees		2009		
23	Rodriguez-	CYGNSS / GNSS-R	500 m - 7	Daily-14	2017	Pacaya-Samiria	All
	Alvarez et		km	days			
	al. (2019)						
24	Rosenqvist	JERS-1 / L-band SAR	100 m	Irregular	1996-	Jaú river basin	All
	et al. (2002)			-	1997		
25	6'1 (2002)		25	T 1	2002	A	A 11
25	Silva et al.	Radarsat-1 / C-band SAR	25 m	Irregular	2003 -	Amazon river (Juruti	All
	(2013)				2005	- Monte alegre)	
26	Sippel et al.	RADAMBRASIL / Side-	0.25	Monthly	1979-	Amazon river in	All
	(1992)	looking Airborne Radar	degrees		1987	Brazil	
27	Souza et al.	Landsat	30 m	Annual	1985-	Brazilian Amazon	Open water
	(2019)				2017		
28	Trigg et al.	LISFLOOD-FP and	180 m /	Daily	1995-	Solimões River	All
	(2009)	HEC-RAS / Hydraulic	irregular		1997	(Itapeua - Manaus)	
		models	C				
29	Wilson et	LISFLOOD-FP /	270 m	Daily	1995-	Solimões River	All
	al. (2007)	Hydraulic model			1997	(Itapeua - Manaus)	
30	Fassoni-	MODIS	250 m	8-Days	2003-	Central Amazon	Open water
	Andrade et				2017		
	al., 2019						

1747 Table S2. Main characteristics of the assessed wetlands.

	Name	Location	Characteristics		
1	Curuai floodplain	Lower Amazon River	Shallow lakes with high suspended sediment concentrations		
2	Janauacá floodplain	Middle Amazon River	Ria lake and "várzea" environments (white-water floodplains)		
3	Uatumã floodplain	300-km reach between Balbina dam and the confluence with the Amazon River	Black-water floodplain		
4	Mamirauá Reserve	Confluence between Solimões and Japurá rivers	Mosaic of chavascal, herbaceous, and low and high várzea vegetation		
5	Purus floodplain	Purus River	Large floodplain to river width ratio		
6	Pacaya-Samiria wetlands	Upper Solimões River	Flooded forests, palm swamps and peatlands		
7	Llanos de Moxos floodable savannas	Upper Madeira River basin	Interfluvial areas among Beni, Mamoré and Madre de Dios rivers		
8	Negro savannas	Negro-Branco interfluvial area	Regional neotectonic depressions		
9	Roraima savannas	Smaller river floodplains interspersed with areas subject to flooding by local rainfall in the upper Branco River basin	Poorly drained interfluvial savannas		

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Table S3. Comparison metrics - Pearson correlation (R) and normalized root mean square error (nRMSD) for timeseries, and Fit metric for the spatial analysis of maximum observed inundation area for all datasets against the

subregional estimates for individual wetland complexes: Curuai (Arnesen et al., 2013), Uatumã (Resende et al., 2019),
Janauacá (Pinel et al., 2019), Mamirauá (Ferreira-Ferreira et al., 2015), Pacaya-Samiria (Jensen et al., 2020), Llanos
de Moxos (Ovando et al., 2016) and Lower Amazon (Park et al., 2019). Four additional subregional datasets were
compared to the local ones mentioned above: Curuai LISFLOOD-FP model (Rudorff et al., 2014), Janauacá
hydrological model (Bonnet et al., 2017), Janauacá TELEMAC-2D model (Pinel et al., 2019), and Llanos de Moxos
ALOS-PALSAR (Ovando et al., 2016). The Fit metric was applied by converting all maps to 1 km, considering a pixel
with inundation fraction higher than 50% as inundated.

																	Lower
						Uatu				Mamira							Amaz
	Dataset	-		Curuai		mã	Janauacá		uá	Pacaya-Samiria		iria	Llanos de Moxos			on	
						2006-				2007-							2000-
	-	Period		2006-2010	)	2011		2007-20	011	2010		2014-2018	8	2001-2014		ļ	2020
			R	nRM	Fit	Fit	R	nR	Fit	Fit	R	nRM	Fit	R	nRM	Fit	Fit
				SD				М				SD			SD		
								SD									
Other	Curuai-	1994-	0.8	12%	0.8	-	-	-	-	-	-	-	-	-	-	-	-
subregio	Model	2015	2		6												
nal	Janauacá	2006-	-	-	-	-	0.7	25	0.49	-	-	-	-	-	-	-	-
datasets	-Bonnet	2019					5	%									
	Janauacá	2006-	-	-	-	-	0.5	17	0.82	-	-	-	-	-	-	-	-
	-Pinel	2015					7	%									
	Llanos	2006-	-	-	-	-	-	-	-	-	-	-	-	0.5	99%	0.3	-
	de	2010												2		3	
	Moxos -																
	ALOS																
Multiple	GIEMS-	1992-	0.9	21%	-	-	0.7	15	-	-	0.8	68%	-	0.9	85%	-	-
datasets	2	2015	6				8	7%			8			1			
at coarse	SWAMP	2000-	0.9	2%	-	-	0.8	38	-	-	0.5	74%	-	0.9	171%	-	-
resolutio	s	2020	1					%			2			2			
n	WAD2	2000-	0.9	82%	-	-	0.7	63	-	-	0.4	2%	-	0.9	123%	_	-
	M	2018	0.5	0270			9	%			6	270		0.5	12070		
N 10 1		1002			0.0	0.61		70	0.00	0.01	0		0.1			0.4	0.45
Multiple	GIEMS-	1993-	-	-	0.9	0.61	-	-	0.80	0.81	-	-	0.1	-	-	0.4	0.45
datasets	D3	2007			2								4			4	
at high	CIFOR	2011	-	-	0.9	0.39	-	-	0.24	0.33	-	-	0.5	-	-	0.3	0.69
					1								5			0	

resolutio	ESA-	1992-	-	-	0.7	0.40	-	-	0.40	0.70	-	-	0.3	-	-	0.1	0.69
n	CCI	2015			6								6			4	
	GIEMS-	1993-	-	-	0.9	0.58	-	-	0.68	0.59	-	-	0.5	-	-	0.3	0.46
	D15	2004			2								1			8	
	GLWD	1992-	-	-	0.8	0.45	-	-	0.79	0.93	-	-	0.6	-	-	0.0	0.51
		2004			8								3			8	
	SWAF-	2010-	-	-	0.9	0.64	-	-	0.63	0.71	0.6	73%	0.2	0.7	213%	0.3	0.57
	HR	2019			5						6		2	5		9	
Hydro-	THMB	1961-	0.7	62%	-	-	0.7	73	-	-	-	-	-	0.5	7%	-	-
logical		2013	2				3	%						4			
models	CaMa-	1980-	0.8	11%	0.9	0.73	0.6	11	0.88	0.83	-	-	0.4	0.8	218%	0.2	0.58
	Flood	2014	0		7		8	1%					9	2		8	
	MGB	1980-	0.8	7%	0.9	0.58	0.6	29	0.82	0.93	-	-	0.5	0.9	26%	0.1	0.52
		2014	3		6		4	3%					2	1		9	
Optical	G3WB	1990-	-	-	0.6	0.29	-	-	0.19	0.14	-	-	0.0	-	-	0.0	0.59
sensors	М	2010			4								3			4	
	GLAD	1999-	-	-	0.8	0.39	-	-	0.30	0.20	-	-	0.0	-	-	0.1	0.78
		2018			4								4			6	
	GSWO	1984-	-	-	0.7	0.31	-	-	0.21	0.17	-	-	0.0	-	-	0.0	0.68
		2019			5								4			9	
SAR	Hess	1995-	-	-	0.9	0.47	-	-	0.28	0.98	-	-	0.4	-	-	0.4	0.69
		1996			6								8			7	
	Chapma	2006-	-	-	0.6	0.27	-	-	0.22	0.68	-	-	0.2	-	-	0.2	0.50
	n	2011			5								8			4	
	Rosenqv	2014-	-	-	0.5	0.34	-	-	0.59	0.98	-	-	0.6	-	-	0.1	0.48
	ist	2018			9								4			9	

1759 Table S4. Long-term minimum inundation areas (km<sup>2</sup>) for 11 wetland complexes (up to three datasets per complex) 1760 and the 18 basin-scale datasets. The local-scale values refer to the following datasets, in this order (comma-separated 1761 values relate to areas with more than one dataset available) : Curuai - ALOS (Arnesen et al., 2013) and LISFLOOD-1762 FP model (Rudorff et al., 2014); Uatumã - ALOS (Resende et al., 2019); Janauacá - ALOS (Pinel et al., 2019), 1763 hydrologic model (Bonnet et al., 2017) and TELEMAC-2D model (Pinel et al., 2019); Mamirauá - ALOS (Ferreira-1764 Ferreira et al., 2015); Pacaya-Samiria - ALOS-2 PALSAR-2 (Jensen et al., 2020); Llanos de Moxos - MODIS (Ovando 1765 et al., 2016) and ALOS (Ovando et al., 2016); and lower Amazon - MODIS (Park et al., 2019). Average, standard 1766 deviation (S.D.) and coefficient of variation (CV) are presented for each area in the last row.

							Llanos					
	Datas					Pacaya-	de	Lower	Amazon		Roraima	Negro
	et	Curuai	Uatumã	Janauacá	Mamirauá	Samiria	Moxos	Amazon	mainstem	Purus	savannas	savannas
	Local	1690,	-	108, 38,	715	3824	1014,	17797				
		1278		18			3962					
Multiple	GIEM	995	263	183	1117	1578	500	19717	26807	349	0	0
datasets	S-2											
at coarse	SWA	2840	479	197	790	4433	24622	38345	53256	3492	309	6375
resolution	MPS											
	WAD	403	97	97	633	20421	31713	14728	29932	4240	258	10443
	2M											
Multiple	GIEM	2712	861	151	1115	2731	8375	33253	44853	2696	383	146
datasets	S-D3											
at high	CIFO	-	-	-	-	-	-	-	-	-	-	-
resolution	R											
	ESA-	-	-	-	-	-	-	-	-	-	-	-
	CCI											
	GIEM	3942	1265	116	1077	3409	15074	44277	59066	3401	2966	2622
	S-D15											
	GLW	-	-	-	-	-	-	-	-	-	-	-
	D											
	SWA	1502	544	69	469	215	8304	20944	30242	784	0	3
	F-HR											
Hydrolog	THM	487	38	1	266	5349	7172	6708	18099	5596	383	195
ical	в											
model	CaMa	2741	861	184	1135	8269	17776	31569	45848	4128	1001	672
	-											
	Flood											
	MGB	3005	212	0	587	6101	4508	21333	32073	1769	226	35
Optical	G3W	-	-	-	-	-	-	-	-	-	-	-
sensors	BM											
	GLA	474	77	8	288	514	1513	6243	9857	335	13	20
	D											
	GSW	736	345	10	314	401	2934	11908	16428	735	117	2
	0											
Synthetic	Hess	2770	584	106	1756	32107	56337	28981	54493	7061	1217	6084
Aperture	Chap	1894	385	68	866	6775	10090	18413	28539	2951	1025	2843
Radar	man											
	Rosen	1514	313	49	422	1077	4566	13413	19512	575	60	5
	qvist											
	Avera	1858	452	89	774	6670	13820	22131	33500	2722	568	2103
	ge											
	S.D.	1148	350	71	430	8978	15190	11637	15551	2094	801	3285
	CV	0.62	0.77	0.80	0.56	1.35	1.10	0.53	0.46	0.77	1.41	1.56
	1	1	1	1		1		1	1	1	1	1

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1769			
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1774 Figure S1. Sensitivity of the fraction used to define a flooded 1km pixel (25% and 50%).





1778 Figure S2. Minimum inundation extent for the central Amazon River, as estimated by the1779 Rosenqvist (years 2015-2016) and Hess (1995) datasets.







Figure S3. Comparison between the long-term maximum inundation for subregional validation
locations (Pinel and Arnesen datasets) as well as the Rosenqvist and Hess datasets for the (a)
Janauacá and (b) Curuai areas. The polygons refer to the area used to extract the values presented
in Tables 3, S3 and S4. The spatial resolution of each dataset is noted.



- 1786
- 1787 Figure S4. Estimation of wetland areas by Gumbricht et al. (2017) across the central Amazon River
- basin. Green pixels relate to the "swamps (incl. bogs)" category, which is defined as "Wet all year
- 1789 around, but not necessarily inundated."
- 1790



1792 Fig S5. Roraima wetlands. Above: Google Earth imagery. Below: Hess SAR classification of1793 floodable areas (at large scale in the left, and detailed scale in the right), displayed as orange areas.





- 1796 Fig S6. Inundation time series for the four wetlands with available datasets, and for the eight basin-
- 1797 scale dynamic datasets (GIEMS-2, SWAMPS, THMB, MGB, WAD2M, CaMa-Flood, SWAF-HR
- 1798 and GIEMS-D3). The subplots that are empty refer to areas where the basin-scale dataset time
- spans did not overlap with the subregional dataset ones. The subregional dataset is displayed in
- 1800 blue, and each of the basin-scale datasets in red.