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Comparison of visible and multi-satellite global inundation datasets at high-spatial resolution

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Abstract

Several new satellite-derived and long-term surface water datasets at high-spatial resolution have recently become available at the global scale, showing different characteristics and abilities. They are either based on visible imagery from Landsat - the Global 3-second Water Body Map (G3WBM) and the Global Surface Water Explorer (GSWE) - or on the merging of passive/active microwave and visible observations - Global Inundation Extent from Multi-Satellite (GIEMS-D3) - that has been downscaled from a native resolution of 25 km×25 km to the 90 m×90 m resolution. The objective of this paper is to perform a thorough comparison of the different water surface

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estimates in order to identify the advantages and disadvantages of the two approaches and propose a strategy for future developments of high-resolution surface water databases. Results show that due to their very high spatial resolution (30 m) the Landsat-based datasets are well suited to retrieve open water surfaces, even at very small size. GIEMS-D3 has a better ability to detect water under vegetation and during the cloudy season, and it shows larger seasonal dynamics. However, its current version overestimates surface water extent on water-saturated soils, and due to its low original (i.e. before downscaling) spatial resolution, it is under-performing at detecting small water bodies. The permanent waters for G3WBM, GSWE, GIEMS-D3 and GLWD represent respectively: 2.76, 2.05, 3.28, and 3.04 million km². The transitory waters shows larger discrepancies: 0.48, 3.72, 10.39 and 8.81 million km².

Synthetic Aperture Radar (SAR) data (from ENVIRONMENT SATellite (ENVISAT), Sentinel and soon the Surface Water Ocean Topography (SWOT)) would be a good complementary information because they have a high nominal spatial resolution and are less sensitive to clouds than visible measurements. However, global SAR datasets are still not available due to difficulties in developing a retrieval scheme adequate at the global scale. In order to improve our estimates of global wetland extents at high resolution and over long-term records, three interim lines of action are proposed: (1) extend the temporal record of GIEMS-D3 to exploit the full time series of microwave observations (from 1978 to present), (2) develop an approach to fuse the GSWE and GIEMS-D3 datasets leveraging the strengths of both, and (3) prepare for the release of SAR global datasets.

Keywords: Wetlands and Inundation, Remote sensing, Landsat, Passive microwaves

2010 MSC: 00-01, 99-00

1 **1. Introduction**

2 The distribution and dynamics of surface water, i.e. permanently and
3 temporarily inundated areas including lakes, rivers, and wetlands, are impor-
4 tant because of their interaction with climate, ecology and human wellbeing.
5 For instance, nearly 30% of global methane emissions (Bousquet et al., 2006)
6 originate from wetland areas, risk management responds to inundation pat-
7 terns (Winsemius et al., 2015), and food security and rice paddy cultivation
8 relies, in certain regions of the world, on surface waters. In return, surface
9 water ecosystems are affected by human activity, land use, hydrologic al-
10 terations, and climate change. The complex feedback mechanisms between
11 surface water and climate are difficult to assess and can potentially exacer-
12 bate the sensitivity and vulnerability of these regions to changes in precip-
13 itation, evapotranspiration, and flow regimes (Gleick, 1989; Chahine, 1992)
14 putting lakes, rivers, and wetlands at risk of rapid deterioration in quantity
15 and quality. Among the many topics about wetlands and climate change, sea
16 level rise and carbon sequestration are major issues. But wetlands are also
17 threatened by land use change and invasive species.

18 Global distribution and dynamics of surface waters at high-spatial res-
19 olution (around 100 m) are still not available, in particular over densely
20 vegetated areas, to satisfy all the needs of the large community of poten-
21 tial users including hydrologists, water and disaster managers, or climate

22 scientists. Indeed, the global, long-term, frequent, and high-resolution char-
23 acterisation of all surface water types is beyond the capabilities of current
24 satellite observations.

25 Visible satellite observations are a primary candidate for the detection of
26 surface waters from space. Moderate Resolution Imaging Spectroradiometer
27 (MODIS) observations have been used to derive global products every two
28 days (<http://oas.gsfc.nasa.gov/floodmap/>) but visible/infrared observations
29 suffer from the presence of clouds (about 70% of Earth surface at any time)
30 (Wilson and Jetz, 2016) and vegetation. Despite the limitations from veg-
31 etation canopy and cloud cover, this type of data is of great value to the
32 community to detect open water. Yamazaki et al. (2015) introduced the
33 Global 3 arc-second Water Body Map (G3WBM) at a pixel resolution of 3
34 arc-seconds (approximately 90 m at the equator) based on Landsat imagery.
35 This dataset exploits multi-temporal acquisitions in order to distinguish per-
36 manent from temporal open water areas. However, no full dynamics of the
37 wetland map are provided. Other datasets have been built from Landsat
38 imagery: (Feng et al., 2014) is global for the year 2000, (Mueller et al., 2016)
39 focused on Australia, (Tulbure et al., 2016) created a three decade dataset
40 over a semi-arid region, and (Verpoorter et al., 2014) mapped an inventory
41 of global lakes. Pekel et al. (2016) recently produced a new Global Surface
42 Water Explorer (GSWE) dataset also from Landsat imagery but using the
43 full 32-year record, allowing for a better description of the trends of surface
44 waters and their occurrence.

45 Synthetic Aperture Radar (SAR) data has the potential to retrieve surface
46 waters at high-spatial resolution ($\simeq 10$ m) as well as capture sub-canopy inun-

47 dation (L-band) as demonstrated by Santoro et al. (2010) using ENVISAT-
48 ASAR, or more recently using the Sentinel 1 mission (Pham-Duc et al.,
49 2017). Although existing SAR retrievals from a number of sensors cover
50 a large extent of the globe, their use for mapping surface inundation has
51 been protracted due to the local calibration needed for accuracy. The past
52 or current availability of the data has not yet allowed for producing a full
53 global high-spatial resolution surface water dataset from SAR data, although
54 such initiatives have been suggested in the past, e.g. (Westerhoff et al., 2013).
55 There is clearly a need to invest more time in retrieval algorithms and po-
56 tentially perform data fusion in order to obtain a global, long-term, reliable,
57 and high-resolution dataset of water extent from this type of observations.

58 The NASA/CNES Surface Water and Ocean Topography (SWOT) mis-
59 sion, planned for launch in 2021, is specifically designed to provide high-
60 spatial resolution ($\simeq 10$ m) and good temporal sampling (22 days repeat)
61 of the extent (and altitude) of continental surface waters (Prigent et al.,
62 2016; Biancamaria et al., 2016) thanks to an interferometric Ka-band radar
63 (Rodriguez, 2015). Although the SWOT data is expected to deliver a new
64 generation of global water surface extents at unprecedented quality and reso-
65 lution, the availability of this product is still years in the future. Meanwhile,
66 alternative efforts should be pursued to provide the community with the best
67 possible information about the spatial and temporal variations of global sur-
68 face water extents. Such efforts would also allow for the extension of the
69 SWOT temporal record backward in time, with existing past imagery; this
70 will be a crucial step in assembling multi-decadal measurements of surface
71 water variation.

72 A possible approach in this direction is to use the synergy from multiple
73 satellite observations. Following this idea, the Global Inundation Extent from
74 Multi-Satellites (GIEMS) database has been developed through a retrieval
75 scheme that combines satellite observations in the visible, near-infrared, and
76 passive/active microwaves (Prigent et al., 2007, 2012; Papa et al., 2010).
77 GIEMS provides a monthly-mean water surface extent at a low spatial resolu-
78 tion ($0.25^\circ \times 0.25^\circ$ equal-area grid) over a 15-year period (1993-2007). In or-
79 der to obtain global inundation estimate at high resolution, downscaling tech-
80 niques have been developed on GIEMS (Aires et al., 2013, 2014). In partic-
81 ular, Fluet-Chouinard et al. (2015) exploited topographic and hydrographic
82 information derived from the Shuttle Radar Topography Mission (SRTM)
83 and trained on a global land cover map to produce a 15 arc-second (~ 500 m)
84 resolution map of the minimum and maximum inundation extents at global
85 scale (GIEMS-D15) (<http://www.estellus.fr/index.php?static13/giems-d15>).
86 In (Aires et al., 2017), an evolution of this downscaling methodology was
87 proposed to obtain a global and dynamic inundation dataset GIEMS-D3, at
88 even higher spatial resolution of 3 arc-second (~ 90 m), over 15 years with a
89 monthly time step.

90 Given the variety of remote sensing approaches, a cross comparison of
91 existing products is needed to explore differences and combined uses of the
92 resulting data. The objective of this paper is to compare and contrast two
93 Landsat-based products (G3WBM and GSWE) and one multi-satellite-based
94 product (GIEMS-D3). Section 2 presents the databases used in this work.
95 A global-scale comparison of the three inundation datasets is performed in
96 section 3, and section 4 presents regional comparisons. To evaluate inherent

97 uncertainties, we contrast the differences among surface water databases with
98 tree and cloud cover data. The advantages and disadvantages of each type
99 of data are then investigated. Finally, section 5 summarises the conclusions
100 of this comparative study. We discuss ways forward to improve estimates
101 of global, high-spatial resolution extents and long-term dynamics of surface
102 waters of multiple types.

103 As the descriptions of original data sources are not always using identical
104 vocabulary, this paper explicitly defines the following terminology: The ex-
105 pression “inundation” refers to all surfaces that are detected as water pixels
106 in the original datasets, including lakes, rivers, temporarily inundated land,
107 but also (by error or not) saturated soils. The expression “transient” is used
108 throughout this paper for non-permanent inundation, including temporal,
109 seasonal, intermittent, and ephemeral inundation, as well as spatio-temporal
110 transitions such as moving river meanders or newly constructed reservoirs.
111 The expression “wetland” is used only in descriptive terms without specific
112 definition and may include all types of inundated areas (such as lakes, reser-
113 voirs, and rivers) but also wet soils or non-inundated areas such as peatlands.

114 **2. Datasets**

115 *2.1. G3WBM*

116 The Global 3 arc-second Water Body Map (G3WBM) uses an automated
117 algorithm to process multi-temporal Landsat images from the Global Land
118 Survey (GLS) database (Yamazaki et al., 2015). Over 33,000 scenes were used
119 from four GLS snapshots at 5-year intervals between 1990 and 2010 in order
120 to delineate a seamless water body map, without cloud and ice/snow gaps.

121 Permanent water bodies were distinguished from transitory water-covered
122 areas by calculating the frequency of water body existence from overlapping,
123 multi-temporal Landsat scenes. By analysing the frequency of water body
124 existence at 3 arc-second resolution, the G3WBM separates river channels
125 and floodplains (<http://hydro.iis.u-tokyo.ac.jp/~yamada/G3WBM/>). De-
126 spite distinguishing between permanent and transitory water surfaces, only
127 permanent waterbodies are believed to be comprehensively mapped, while
128 not all transitory waterbodies are captured by the four used used scenes (Ya-
129 mazaki et al., 2015). The seven different G3WBM surface types are described
130 in Tab. 1 and classes 1-4 represent transitory types.

131 2.2. GSWE

132 The Global Surface Water Occurrence (GSWE) dataset (Pekel et al.,
133 2016) uses three million Landsat satellite images to quantify inundation over
134 32 years (from 1984 to 2015) at a 30 m spatial resolution. The GSWE dataset
135 is freely available at: <https://global-surface-water.appspot.com/>. Each Land-
136 sat pixel has been classified as open water, land, or non-valid observation
137 using an expert system. Open water is defined as any feature of water larger
138 than $30\text{ m} \times 30\text{ m}$ open to the sky, including fresh and saltwater. Validation
139 against Google Earth images (i.e. from satellite datasets covering mostly
140 the last three years from visible instruments such as Landsat) and labelling
141 from experts shows that the classifier produces less than 1% of false water
142 detections, and misses less than 5% of water. About 52% of the maximum
143 inundation extent (over the 32 years) is found above 44°N . In 2015, perma-
144 nent bodies of water represented about 2.78 million km^2 , with 86% of that
145 area present throughout the 32-year period (Pekel et al., 2016). A rigorous

	G3WBM	GLWD
Class	(Yamazaki et al., 2015)	(Lehner and Döll, 2004)
1	Snow	Lake
2	Wet Soil, Wet Vegetation, Lava	Reservoir
3	Salt Marsh	River
4	Temporally Flooded Area	Freshwater Marsh, Floodplain
5	Permanent Water	Swamp Forest, Flooded Forest
6	Permanent Water (from SWBD)	Coastal Wetland
7	Ocean (external land/sea mask)	Pan, Brackish/Saline Wetland
8		Bog, Fen Mire (Peatland)
9		Intermittent Wetland/Lake
10		50–100% Wetland
11		25–50% Wetland
12		0–25% Wetland

Table 1: The seven surface classes of the G3WBM dataset, and the twelve classes of GLWD (classes 1-3 corresponds to open water, 4-12 to wetlands).

146 validation has been performed based on over 40,000 Landsat-derived control
147 points spanning all three Landsats operational life spans dating back to 1985.

148 When using visible observations, instantaneous estimates can be contam-
149 inated by error, for instance due to the presence of clouds (only clear pixels
150 are used to compute the occurrence, but this cloud detection can be erro-
151 neous). Other potential errors and issues need also to be covered, i.e. omis-
152 sion errors, algorithmic issues, and permanent water that was not present at
153 all times during the 32-year period, such as newly built reservoirs or river
154 meanders that have moved. Therefore, a threshold in occurrence of inun-
155 dation is needed in order to distinguish permanent from transitory pixels.
156 The GSWO (Global Surface Water Occurrence) product provides the surface
157 open water occurrence “O(surface water)” over the 32-year Landsat record.
158 This occurrence was obtained using only cloud-free pixels. This clear-sky
159 sampling aliasing increases the importance of the dry seasons and decrease
160 that of the wet seasons. To alleviate this difficult, the occurrence in GSWE
161 was normalised by month of the year. Note that the sampling during the day
162 should still exclude boreal winter in the GSWO occurrence. *In the following,*
163 *we will refer to GSWO for the occurrence product of the GSWE dataset.*

164 For the purpose of conducting baseline comparisons as conducted in this
165 paper, we use:

- 166 • The threshold of $O(\text{surface water}) \geq 90\%$ for permanent waters.
- 167 • and $O(\text{surface water}) < 90\%$ to identify transitory waters over the full
168 32-year record in order to accommodate some uncertainties.

169 This definition of permanency differs significantly from (Pekel et al., 2016)

170 who produced permanent water estimates only for shorter time periods (per-
171 manent waters are defined at the yearly scale, not at the 32-year scale).
172 The 0.9 threshold appears as a good pragmatic compromise: With a too
173 low threshold, seasonal waters would be classified as permanent, and with
174 a too high threshold, erroneous classifications would suppress truly perma-
175 nent pixels. Erroneous classifications can be related for instance to omission
176 errors, vegetation and algorithmic issues, and to include permanent water
177 that was not present at all times during the 32 year periods, such as newly
178 built reservoirs or river meanders that have moved. Note that by using a
179 90% threshold on the occurrence, if a dam is constructed for less time than
180 the 10% of the full record, it will not be a permanent water body but a
181 transitory. If we had chosen a 100% threshold, then even less such structures
182 would be kept as permanent waters. It should be noted however that the
183 selection of this threshold, which only represents our best guess in the ab-
184 sence of conclusive and consistent evidence, will affect the results presented
185 in this study. However, the maximum water extent (permanent plus transi-
186 tory) is independent of this threshold. Other threshold or no threshold could
187 be considered instead.

188 *2.3. GIEMS and GIEMS-D3 databases*

189 To minimise limitations and uncertainties related to measurements by
190 individual instruments, a multi-sensor technique has been developed to esti-
191 mate surface water extent and dynamics at global scale (Prigent et al., 2007,
192 2012; Papa et al., 2010). The method exploits the complementary sensitiv-
193 ities of different satellite observations to surface characteristics (e.g., water,
194 vegetation, soil). Passive microwave observations are particularly sensitive

195 to the presence of surface water, even under vegetation canopy. However,
196 additional observations have to be used to subtract the contribution of con-
197 founding factors such as vegetation from the signal and to avoid confusion
198 with other surface types such as dry sand. The following satellite observa-
199 tions were used to generate GIEMS: (1) passive microwaves from the Special
200 Sensor Microwave/ Imager (SSM/I) measurements between 19 and 85 GHz;
201 (2) active microwave backscattering coefficients at 5.25 GHz from scatterom-
202 eters; and (3) visible and near-infrared reflectances and the derived NDVI
203 (Normalized Difference Vegetation Index). The methodology is described in
204 details in (Prigent et al., 2001). The use of multiple satellite sources is a
205 true challenge, e.g. it is required to obtain a well calibrated dataset for each
206 individual source. But it was shown that the GIEMS approach is able to
207 benefit from the synergy of these satellite sources to obtain a general algo-
208 rithm able to perform well in most environments. GIEMS data have been
209 used for modelling of surface water dynamics and biogeochemical fluxes and
210 have been thoroughly evaluated. Note that GIEMS estimates include all
211 surface waters such as rivers, floodplains or lakes indiscriminately. The in-
212 undation is expressed as the fractional inundation within each 773 km^2 pixel
213 of an equal-area grid with 0.25° resolution at the equator. Regional qual-
214 ity assessments of the GIEMS database using SAR data indicate that the
215 approach captures realistically complex wetlands. However, it can underesti-
216 mate small surface waters comprising less than 10% fractional coverage of a
217 grid cell ($\leq 80 \text{ km}^2$) due to its coarse spatial resolution and it can also overes-
218 timate large surface waters comprising more than 90% of fractional coverage
219 due to water-saturated soils (Prigent et al., 2012). GIEMS is available at

220 (<http://lerma.obspm.fr/spip.php?article911lang=en>).

221 Downscaling methods have recently been developed to reduce the spatial
222 resolution of GIEMS estimates from 25 km to 500 m (15 arc-second, GIEMS-
223 D15) (Fluet-Chouinard et al., 2015) (<http://www.estellus.fr/index.php?static13/giems->
224 [d15](http://www.estellus.fr/index.php?static13/giems-d15)) and 90 m (3 arc-second, GIEMS-D3) (Aires et al., 2017). The method-
225 ology uses a floodability index which is predicted for each pixel based on
226 topography and hydrography information from the HydroSHEDS database
227 (Lehner et al., 2008). This floodability index at high-spatial resolution is
228 used to distribute the water fraction from coarse resolution into the high-
229 resolution pixels. A smoothing procedure is applied during the downscaling
230 to reduce transition artefacts at the edges of the low-resolution boxes from
231 GIEMS. GIEMS-D3 has been assessed by analysing its spatial and tempo-
232 ral variability, and evaluated by comparisons to other independent satellite
233 observations (Aires et al., 2017). Topographic information is useful in pre-
234 dicting natural inundation where hydrology is controlled by elevation, but
235 is more limited in human-modified areas (e.g. artificial reservoirs or rice
236 paddies). The probability of surface water “P(surface water)” is defined in
237 GIEMS-D3 as the temporal recurrence (in percent per high-resolution pixel)
238 of observed water in the available monthly time series (1993-2007).

239 *2.4. Auxiliary datasets*

240 *2.4.1. GLWD*

241 The Global Lakes and Wetlands Database (GLWD) represents a compre-
242 hensive dataset of global surface water area, including small and large lakes,
243 reservoirs, rivers, and wetlands (Lehner and Döll, 2004). GLWD was gener-
244 ated through a compilation and assimilation of existing analog and digital

245 maps and cartographic products, and due to the historic perspective of the
246 majority of data included, it is assumed to represent maximum open water
247 and wetland extents. In comparison to water and wetland extents from land
248 cover maps, it is the most extensive water mask of its kind (Nakaegawa,
249 2012). The “level 3” dataset of GLWD that is used here provides a global
250 30 arc-second resolution grid describing twelve different surface water types
251 (see Tab. 1). GLWD is static and offers little information on seasonality.

252 *2.4.2. Tree density*

253 In order to assess the surface water retrieval from visible observations
254 when vegetation is present, the global percent tree cover map by (Hansen
255 et al., 2009) is used. The MODIS vegetation continuous fields algorithm
256 and a supervised regression algorithm were applied to estimate the percent
257 tree cover over 500 m pixels. Results show that MODIS data yield greater
258 spatial detail in characterising the tree cover compared to past efforts using
259 for instance AVHRR data. Furthermore, validation efforts have shown a
260 reasonable agreement between the MODIS-estimated and the observed tree
261 cover over validation sites.

262 *2.4.3. Cloud fraction*

263 A cloud fraction dataset can be used over land to investigate where vis-
264 ible observations (from Landsat) can actually retrieve surface parameters
265 or not. Cloud cover dynamics are captured over a large extent yet at fine
266 spatial grain twice-daily by the MODIS satellite images. A near-global, fine-
267 resolution ($\simeq 1$ km) monthly cloud frequency dataset is presented in (Wil-
268 son and Jetz, 2016) (<http://www.earthenv.org/cloud>), spanning a temporal

269 range over 15 years.

270 Note that the tree density and the cloud fraction datasets are derived
271 from the same instrument, MODIS, but their processing are independent
272 from each other.

273 **3. Global comparison**

274 *3.1. Surface water extents and probabilities*

275 Fig. 1 presents a comparison of the G3WBM and GSWE Landsat-derived
276 datasets, along with the GIEMS-D3 multi-satellite estimate, at the global
277 scale at 90 m spatial resolution. The three estimates share the major hydro-
278 logical structures, with large surface water extents in Canada, Bangladesh,
279 or Eastern Argentina.

280 The two Landsat-derived products provide similar results over the boreal
281 region with permanent surface water in large areas in Canada, over Scan-
282 dinavia and in Siberia. The surface water occurrence (for GSWO) and sur-
283 face water probability (GIEMS-D3) (as defined in the data section) in these
284 regions is generally lower with GIEMS-D3. The differences can be partly
285 related to the reference time periods to calculate the inundation statistics.
286 Landsat only provides information under daylight conditions. As explained in
287 the data section, the GSWO dataset provides statistics done at the monthly
288 level so each month has the same weight in the overall statistics, indepen-
289 dent of the number of valid observations in each month. However, during
290 the boreal winter, no observation is available in the Landsat products due
291 to lack of daylight which does not allow for the calculation of inundation
292 occurrence. On the other hand, the GIEMS-D3 product is essentially based

293 on microwave observations that are available regardless of light conditions.
294 The reference time period for the inundation probability includes the winter
295 months when snow and ice cover the boreal region (this is not considered to
296 be inundated in GIEMS-D3). As a consequence, the surface water probab-
297 ity is systematically lower with GIEMS-D3 than the GSWO occurrence in
298 these regions.

299 Compared to the GIEMS-D3 estimates, the Landsat-derived water esti-
300 mates are more uniformly spread, with small surface water detected in most
301 environments all over the globe. The GIEMS-D3 data is based on the low
302 spatial resolution GIEMS product which has known difficulties in detecting
303 water surfaces that cover less than 10% of the original $0.25^\circ \times 0.25^\circ$ pix-
304 els. The downscaling methodology partly compensates for these omissions
305 through fusion with GLWD data (Aires et al., 2017), yet in general these
306 omissions are propagated into the higher resolution version.

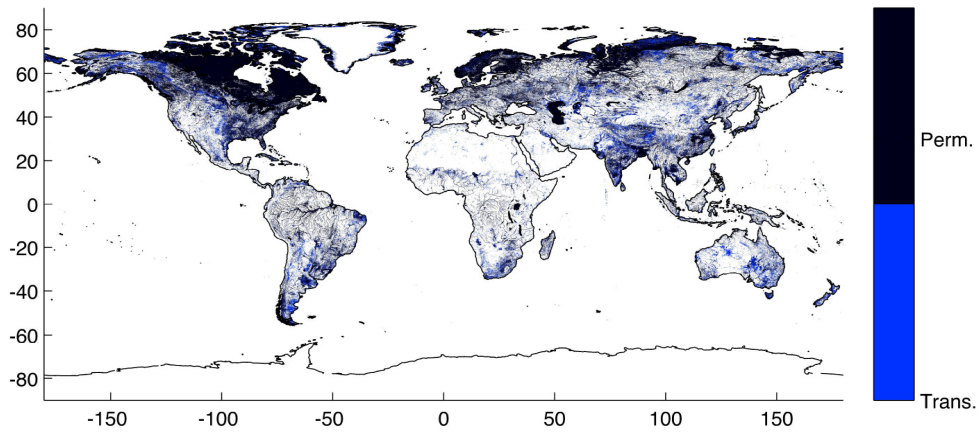
307 In contrast, GIEMS-D3 detects larger areas of surface water than the
308 Landsat estimates in equatorial forests, e.g. around the Amazon or the Congo
309 Rivers. The microwave observations used to derive the GIEMS product can
310 partly penetrate through the dense canopy whereas the Landsat measure-
311 ments are blocked by the vegetation.

312 In Australia and in South Africa, significant differences are observed be-
313 tween the similar Landsat products and GIEMS-D3. More inundation is
314 detected in South Africa with Landsat than with GIEMS-D3, while in the
315 north of the Western Territories in Australia the opposite prevails with larger
316 inundation detected by GIEMS-D3. Significant differences are also observed
317 between the G3WBM and the GSWO products around Lake Mackay. This is

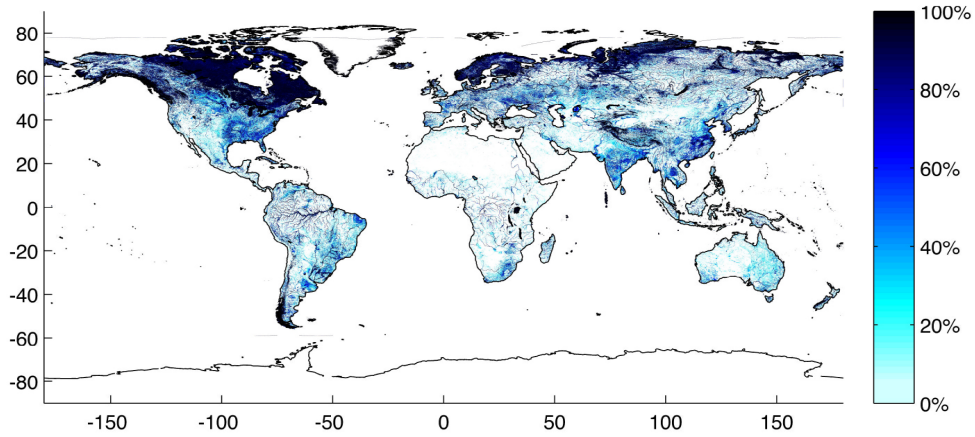
318 likely related to the difference in the processing record for these two products
319 (32 years for GSWO and only four observations for G3WBM).

320 *3.2. Permanent and transitory surface water*

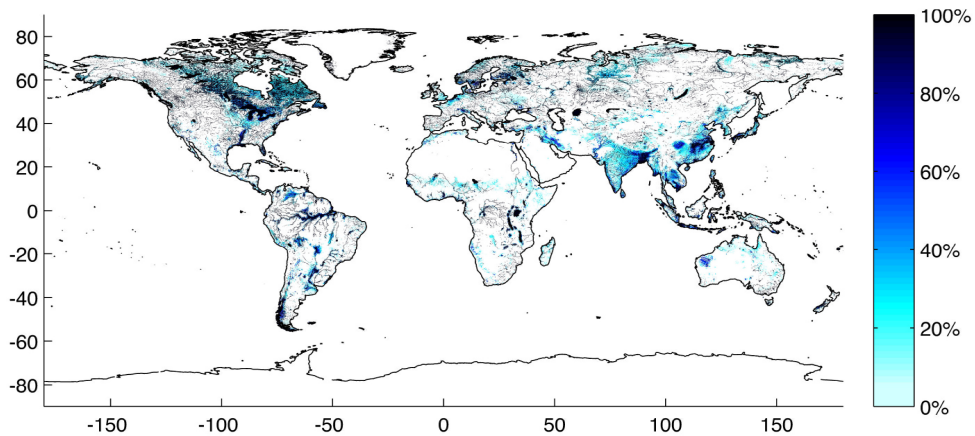
321 For further comparisons, Fig. 2 shows only the permanent water bodies
322 for G3WBM, GSWO ($O(\text{surface water}) > 0.9$), and GIEMS-D3 ($P(\text{surface}$
323 $\text{water}) = 1$), along with the difference between GSWO and GIEMS-D3. To
324 improve the visual interpretation, the fraction of permanent inundation is
325 aggregated into each $0.1^\circ \times 0.1^\circ$ pixel. Furthermore, the same HydroSHEDS
326 land/sea mask has been applied to all datasets to avoid discrepancies along
327 the marine coastlines and to exclude the Caspian Sea from all calculations.
328 Overall, the three maps show generally good spatial agreement, with a total
329 permanent surface water extent of 2.76 million km^2 for G3WBM, 2.05 mil-
330 lion km^2 for GSWO, and 3.28 million km^2 for GIEMS-D3 (Tab. 2). The
331 estimate of GSWO increases to 2.78 million km^2 when using a single year
332 (i.e. 2015) and an O-threshold of 100% instead of the 32-year record with
333 an O-threshold of 90%. All results are reasonably close to the reference data
334 of GLWD (3.04 million km^2). It can be seen in the difference map (D) that
335 in the tropical regions, GIEMS has higher water surfaces (blue colour) prob-
336 ably because it has the ability to better detect water through the presence
337 of clouds or vegetation. Conversely, in higher latitudes, GSWO tends to
338 show more water surfaces (red colour), probably due to spatial resolution
339 limitations in GIEMS-D3. These hypotheses will be further discussed in the
340 following. It should be noted, however, that the interpretation of permanent
341 water is not identical in the three datasets as GIEMS-D3 includes inundation
342 that is not visible from the sky (i.e. beneath vegetation).



(a) G3WBD Classification



(b) GSWO Occurrence



(c) GIEMS-D3 Probability

18
 Figure 1: (a) G3WBM classification into permanent and transitory inundation (0-1), (b) the GSWO inundation occurrence (0-100%), and (c) the GIEMS-D3 inundation probability (0-100%). The rendering of this figure is difficult at very high spatial resolution (90 m), the maximum water extents are respectively: 3.74, 5.77 and 13.67 million km² (Tab. 2).

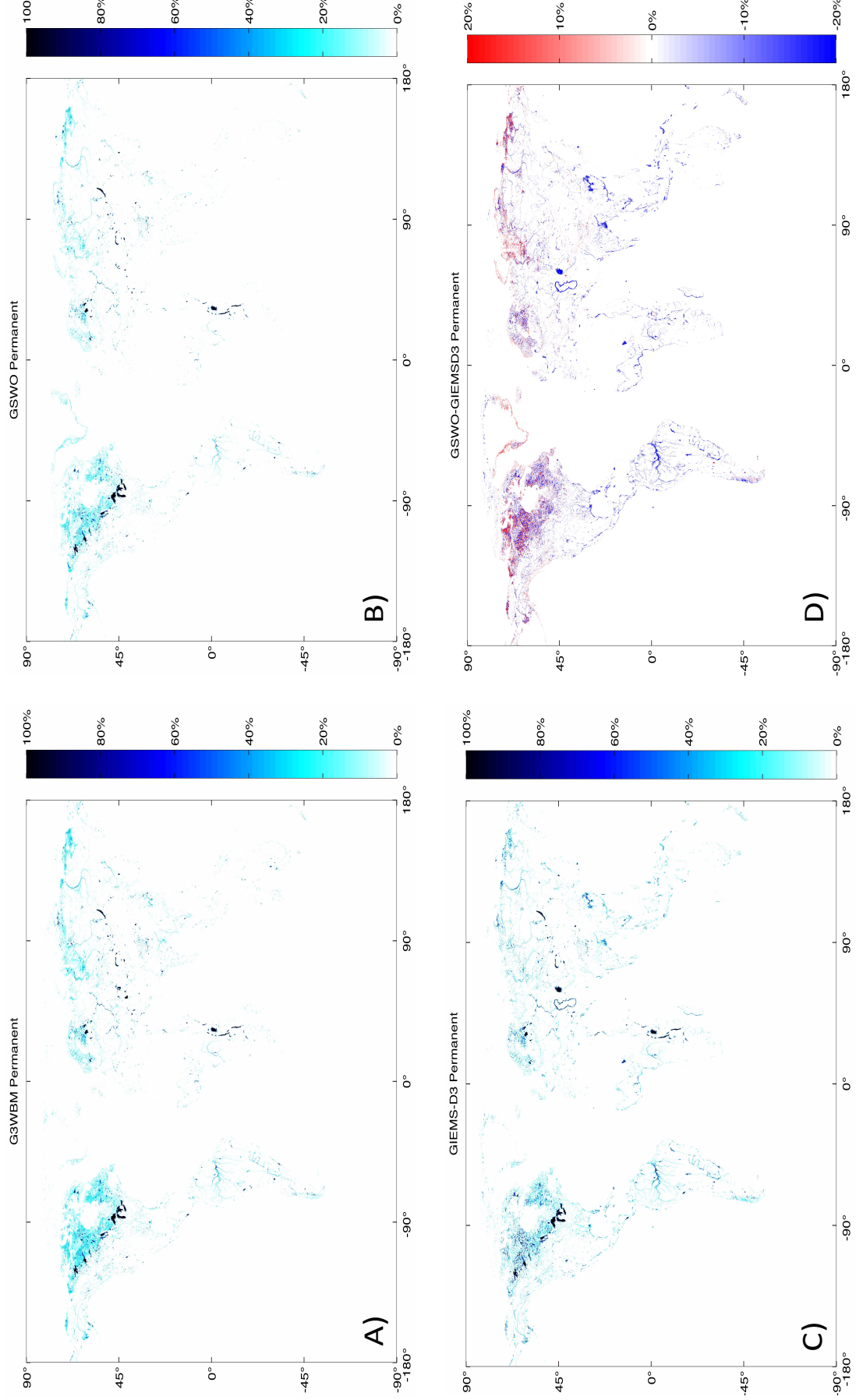


Figure 2: Area-fraction (in %) of permanent inundation states over $0.1^\circ \times 0.1^\circ$ pixels for G3WBM (A), GSWO (B), and GIEMS-D3 (D). The last figure represents the area differences (in %) of GSWO minus GIEMS-D3 (D).

	G3WEM	GSWE	GIEMS-D3	GLWD	
Reference	(Yamazaki et al., 2015)	(Pekel et al., 2016)	(Aires et al., 2017)	(Lehner and Döll, 2004)	
Observations	Landsat	Landsat	downscaled / multi-sensor	compiled maps & charts	
Period	1990, 1995, 2000, 2001	1984-2015	1993-2007	Pre-1990s	
Resolution	3 arc-sec	1 arc-sec	3 arc-sec	30 arc-sec	
Detect	Open water bodies	Open water bodies	All surface inundation	Waterbodies & natural wetlands	
Product(s)	Surface type (see Tab. 1)	Occurrence, water occurrence change intensity, seasonality, annual water recurrence, water transitions, maximum water extent	Inundation probability, 15-years time record of monthly binary inundation state	Surface type (see Tab. 1)	
Validation	Visual quality control Comparison to National Hydrography Dataset	40,000 Landsat control points dating back to 1985 for the 3 Landsats	Comparison to other inst. (SAR, MODIS, Landsat) & other products (River height, river discharge)	Against documented databases	
Permanent	Open-water	2.76	2.05	2.78	3.04
	Inundation				
Transitory	Open-water	0.48	3.72	0.81	8.81
	Natural wetlands				
	Inundation (w. rice)				
Total		3.24	5.77	13.67	11.85

Table 2: Estimates of permanent and transitory water extents (in million km²) according to the three investigated datasets, and GLWD for reference. For GSWE, results are provided for the full 32-year record (using O > 90% as threshold for permanent waters) and for 2015 only (using O = 100%). Permanent water of GLWD is derived from classes 1-3 only (see Tab. 1). Some numbers are different from the original papers due to inland-water/ocean classification or because of the effects of the threshold selected here. Areas

343 Fig. 3 presents the transitory water bodies: classes 1-4 from G3WBM,
344 $O(\text{surface water}) \leq 0.9$ for GSWO, and $P(\text{surface water}) < 1$ for GIEMS-D3.
345 Here, much larger differences can be observed between the three products.
346 The total transitory surface water is 0.48 million km^2 for G3WBM, 3.72 mil-
347 lion km^2 for GSWO, and 10.39 million km^2 for GIEMS-D3, compared to
348 8.81 million km^2 for GLWD (Tab. 2). Despite the common use of Landsat
349 imagery, G3WBM detects much less transitory surface water than GSWO,
350 which can be attributed both to differences in the observation period and
351 the detection algorithms. The more extensive temporal coverage of GSWO
352 is more likely to capture seasonal variations than the fewer composite snap-
353 shots used for G3WBM.

354 Disagreements between GSWO and GIEMS-D3 transitory water bodies
355 have different origins, depending on the environment. First, all over the
356 globe, small transitory water bodies are detected by GSWO and are likely
357 missed by GIEMS-D3 due to the low detection limit of the original GIEMS
358 data. Second, in Asia, GSWO detects much less transitory water surfaces
359 than GIEMS-D3. Local analyses in the Ganges-Brahmaputra region (Papa
360 et al., 2015) or in the Mekong Delta (see estimates from Sakamoto et al.
361 (2007)) show that GIEMS tends to over-estimate the surface water in areas
362 with saturated soils and irrigated rice culture. However, in these regions, vis-
363 ible and near-infrared observations can also have difficulties in detecting and
364 correctly classifying mixed surfaces with some vegetation coverage (Sakamoto
365 et al., 2007; Crétaux et al., 2016). Hence in the GSWO dataset, some inun-
366 dated pixels that are partly covered by vegetation may not be detected. In
367 addition, these regions are under very persistent cloud cover, especially dur-

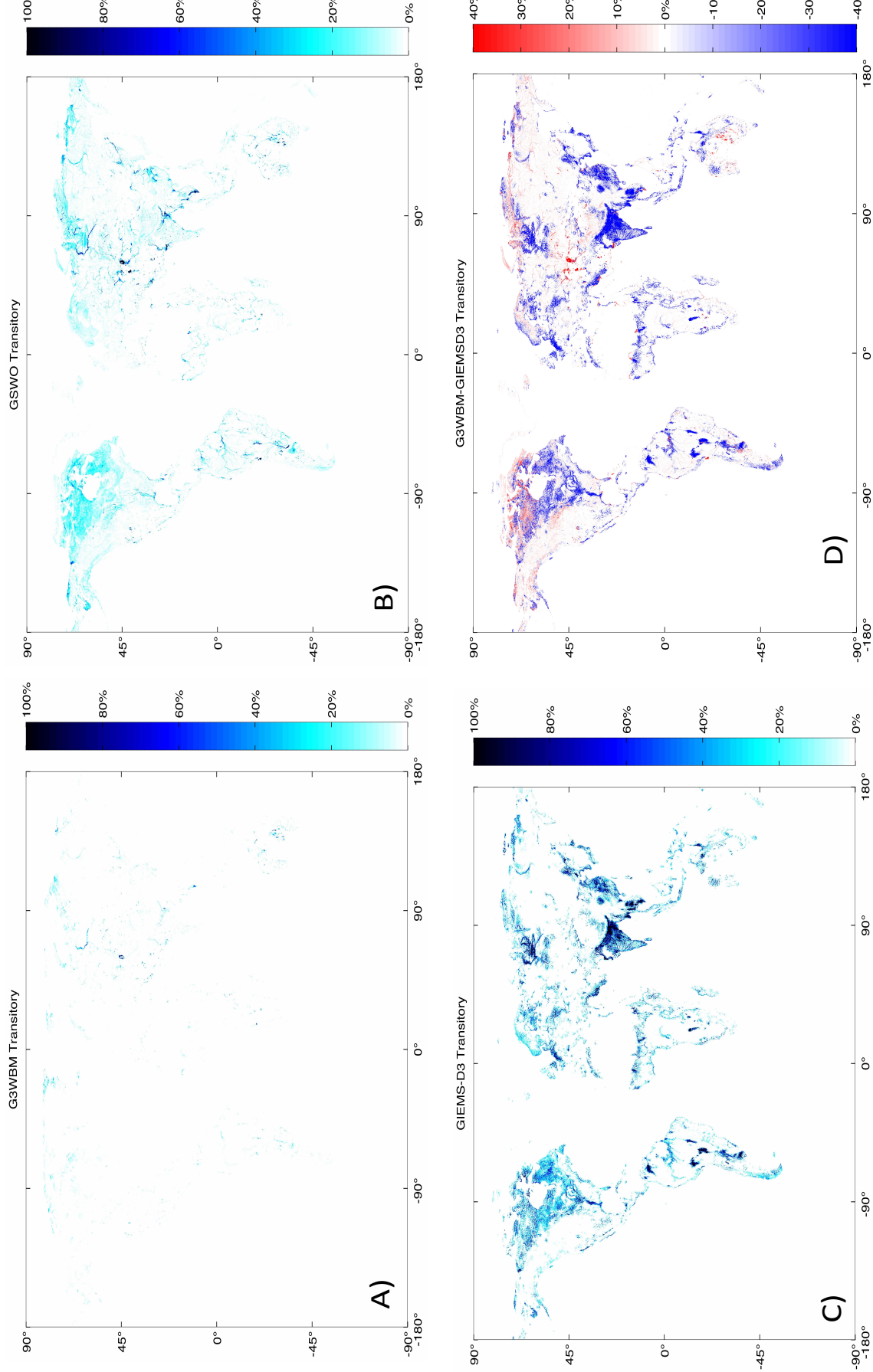


Figure 3: Area-fraction (in %) of transitory inundation states over $0.1^\circ \times 0.1^\circ$ pixels for G3WBM (A), GSWO (B), and GIEMS-D3 (C). The last figure represents the area differences (in %) of GSWO minus GIEMS-D3 (D).

368 ing the wet season. Landsat observations cannot be used efficiently in these
369 conditions to detect the presence of water, limiting drastically the possible
370 detection of transitory surface water. Third, around extensive hydrological
371 land-water systems (e.g., the Mississippi, Orinoco or Amazon Rivers and
372 floodplains, or the Pantanal wetlands), the GSWO transitory water bodies
373 occupy less area than in GIEMS-D3. With Landsat observations hampered
374 by vegetation and clouds, an underestimation of the transitory water bodies
375 can be expected in particular for densely vegetated areas prone to large cloud
376 cover. Finally, at high latitudes, differences between GSWO and GIEMS-D3
377 likely result from the combination of two factors: the lack of spatial reso-
378 lution in the original GIEMS data to detect very small lake fractions and
379 the difference in the reference period to calculate the temporal statistics of
380 surface water (with or without the boreal winter).

381 The longitudinal and latitudinal distribution of surface water extents are
382 illustrated in Fig. 4 for permanent and transitory surface waters of all three
383 estimates (G3WBM, GSWO, and GIEMS-D3). The agreement of the per-
384 manent surface water extents is reasonable, with slightly higher values for
385 GSWO in the tropical regions, especially in South America. The slight under-
386 estimation around the equator of Landsat estimates with respect to GIEMS-
387 D3 is expected to be related to the rain forest or clouds that block the visible
388 and near infrared observations. Transitory water bodies, on the other hand,
389 show much weaker agreement among sources, with substantially more transi-
390 tory water surfaces from GIEMS-D3 in comparison to G3WBM and GSWO,
391 especially over higher latitudes in North America and Eurasia. These spa-
392 tial differences can also be observed in Figs. 2(D) and 3(D). More detailed

393 explanations on these differences will be given in the following sections.

394 Fig. 5 presents histograms of the probability distribution function for per-
395 manent and transitory surface water extents over $0.1^\circ \times 0.1^\circ$ pixels, at differ-
396 ent latitudinal bands. G3WBM and GSWO estimates reveal strong agree-
397 ment for permanent water bodies, regardless of the environment. GIEMS-D3
398 shows slightly less pixels with a smaller percentage of permanent water cover-
399 age (below 5%), across all latitudinal sections, yet slightly more with a higher
400 percentage (above 10%). The increase in the probability for the surface wa-
401 ter percentage close to 100% for all products is due to water bodies (mostly
402 lakes) larger than the $0.1^\circ \times 0.1^\circ$ grid used for the calculation. For the tran-
403 sitory water surfaces, the pattern of under-detected small water fractions
404 and exceeding large water fractions by GIEMS-D3 compared to the other
405 products is more prominent.

406 A $0.1^\circ \times 0.1^\circ$ pixel-to-pixel comparison of the GSWO and GIEMS-D3
407 datasets (from Fig.s 2 and 3) is provided in Fig. 6. The first row represents
408 the GSWO/GIEMS-D3 confusion matrices for permanent (left) and tran-
409 sitory (right) water extents (in percentage between 0 and 1). The colorbar
410 represents the logarithm of the number of $0.1^\circ \times 0.1^\circ$ samples in each 0.1×0.1
411 bin of the plot. We observe that for permanent water surfaces, this matrix is
412 quite diagonal. This means that there is no notable difference between the
413 two datasets, except for the differences that can result from random errors
414 in both datasets. For the transitory pixels, GSWO has a reduced range of
415 water extent percentages (x-axis), whereas GIEMS-D3 shows a much broader
416 range and increasing frequencies of high water surface percentages. This can
417 be explained by the fact that vegetated fractions in the $0.1^\circ \times 0.1^\circ$ pixels can

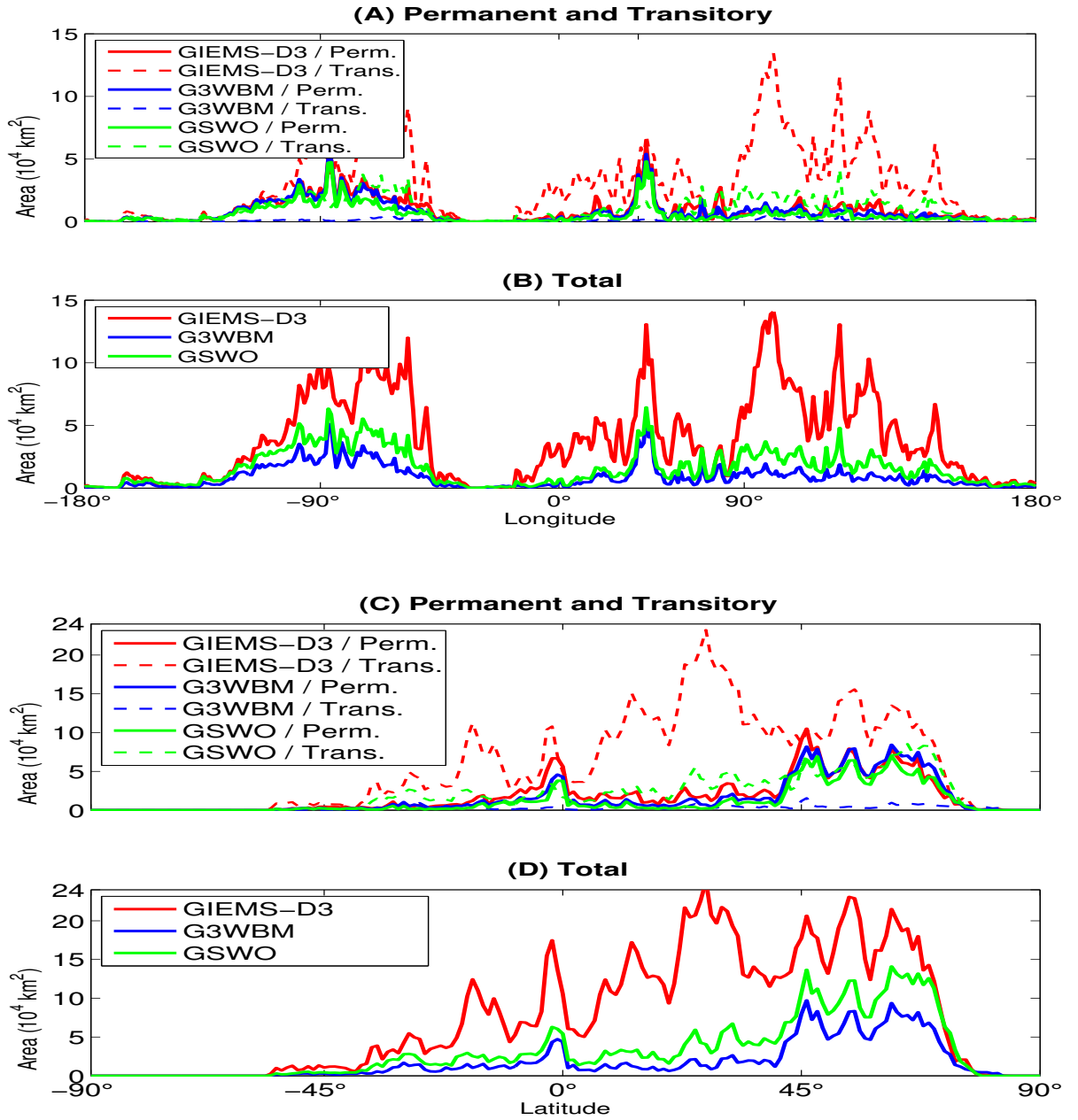


Figure 4: Averaged longitudinal (A and B) and latitudinal (C and D) surface water extents (in 10^4 km^2 per 1° bin), for G3WBM, GSWO, and GIEMS-D3 estimates. Distributions are plotted for permanent and transitory surface water extents, and for their sum.

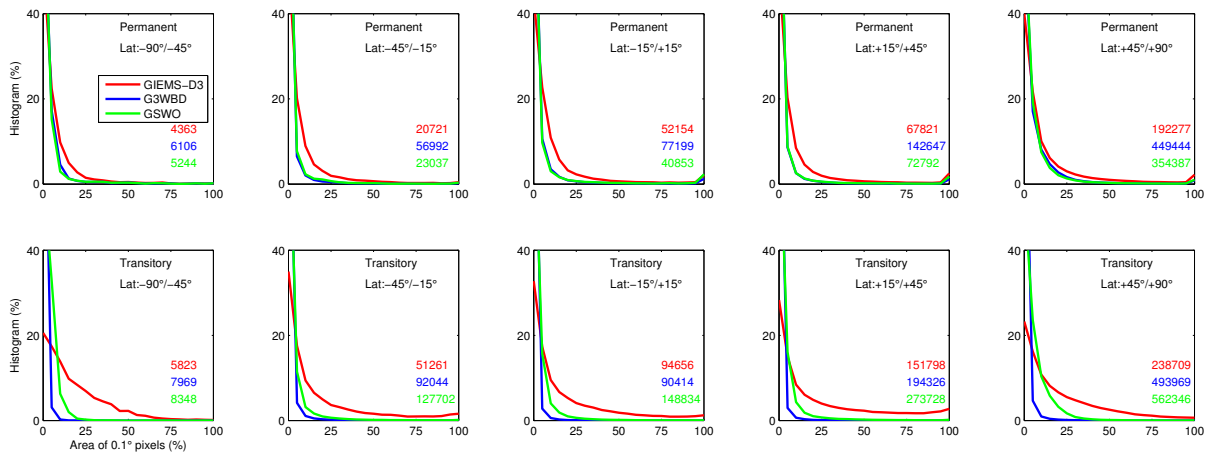


Figure 5: Histograms of the permanent (top row) and transitory (bottom row) surface water percentage over $0.1^\circ \times 0.1^\circ$ pixels, for GIEMS-D3 (red), G3WBM (blue), and GSWO (green). From left to right: for $-90^\circ/-45^\circ$, $-45^\circ/-15^\circ$, $-15^\circ/+15^\circ$, $+15^\circ/+45^\circ$, and $+45^\circ/+90^\circ$ latitudinal bands. The number of $0.1^\circ \times 0.1^\circ$ pixels for each dataset is also indicated.

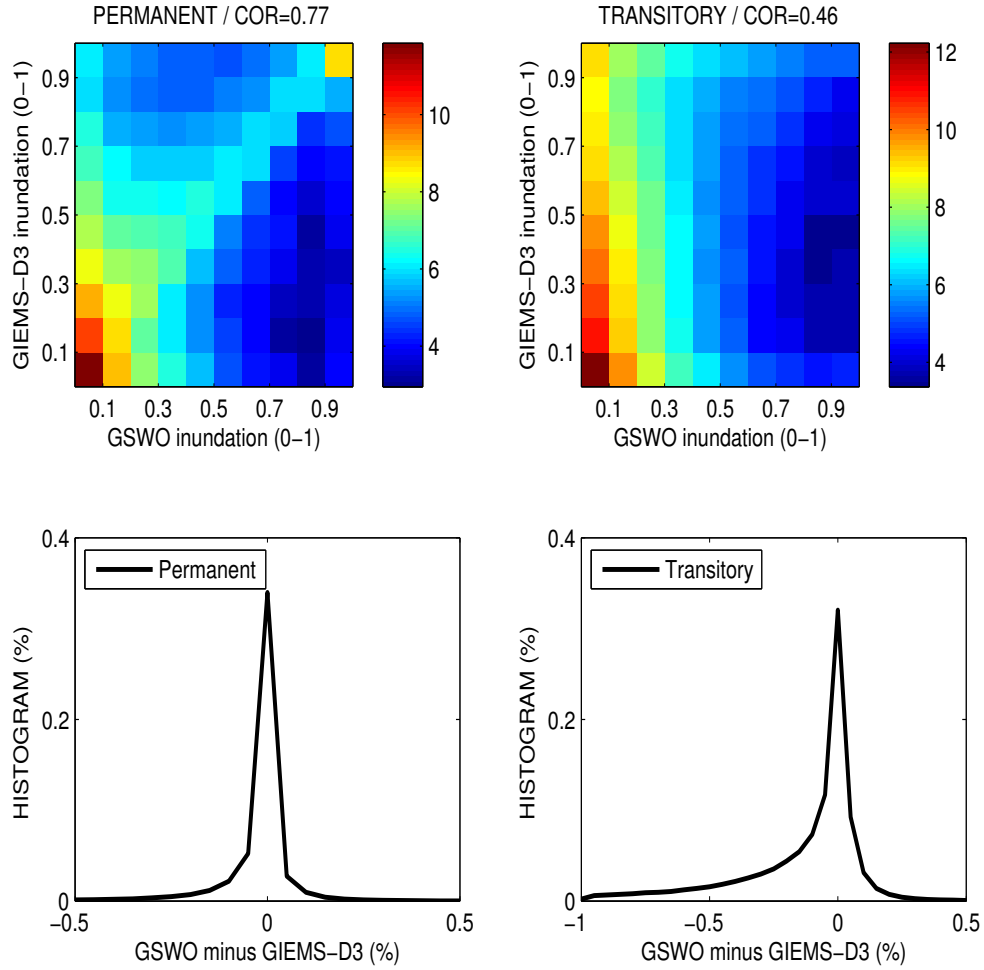


Figure 6: Pixel-to-pixel ($0.1^\circ \times 0.1^\circ$) comparison of the GSWO and GIEMS-D3 datasets, for permanent (left) and transitory (right) surface waters. First row: GSWO/GIEMS-D3 confusion matrices for permanent (left) and transitory (right) water extents (in percentage between 0 and 1). The colorbar represents the logarithm of the number of $0.1^\circ \times 0.1^\circ$ samples in each 0.1×0.1 bin of the plot. Second row: corresponding histogram of differences between the GSWO and GIEMS-D3 water extent estimates (percentages are expressed with the 0-1 range).

418 be detected in GIEMS-D3, but not in GSWO. This will be examined in more
419 detail in the following sections. The lower row represents the corresponding
420 histograms of differences between the GSWO and GIEMS-D3 water extent
421 estimates. For the permanent waters, this distribution is centred around zero,
422 and the distribution is symmetric meaning that no dataset is over-estimating
423 the water extent compared to the other. For the transitory water extents, the
424 distribution is skewed with a long tail to the left meaning that GIEMS-D3
425 has more pixels with high transitory water extents.

426 **4. Regional evaluation**

427 In order to investigate the advantages and disadvantages of the various
428 inundation datasets, a regional analysis is performed in this section over
429 several contrasted environments.

430 *4.1. The Amazon River in a tropical forest environment*

431 Fig. 7 presents a comparison between Landsat estimates from G3WBM
432 and GSWO, the GIEMS-D3 probabilities, and the GLWD classification, over
433 the Amazon Basin. Tree cover density is also shown to support interpre-
434 tation. Overall, this figure supports the general findings of the global-scale
435 comparison (Fig. 1). The spatial structure of the inundation pattern is quite
436 similar for all three satellite datasets and they exhibit very realistic distri-
437 butions of major rivers and tributaries (Amazon, Solimoes, Negro, Tapajos,
438 Tocantins) as well as major associated inundated areas and wetlands. This
439 finding aligns with several previous studies where GIEMS was intensively
440 evaluated over the Amazon Basin (Papa et al., 2008, 2013; Frappart et al.,

441 2012; Getirana et al., 2012). Nevertheless, on a finer spatial scale, clear dif-
442 ferences can be observed in the morphological patterns, especially over the
443 flooded zones of the Rio Negro Basin (2°S - 2°N ; 64°W - 61°W), the Madeira
444 Basin (15°S - 7°S ; 69°W - 62°W), or the floodplains adjacent to the main chan-
445 nel of the Amazon River. These regions are characterised by extensive sa-
446 vanna or forest floodplains with dense vegetation canopies that are inundated
447 for four to six months each year (Fig. 7e).

448 To better illustrate the correlation between Landsat retrieval and vegeta-
449 tion, Fig. 8 compares the GSWO and GIEMS-D3 inundation probabilities for
450 ten tree density ranges (0-10% to 90-100%), over a $5^{\circ} \times 5^{\circ}$ cell in the Amazon
451 region (5°S - 0°S ; 70°W - 65°W). The fraction of pixels classified as inundated
452 is estimated for each tree density bin. It can be seen in Fig. 7e that the
453 tree density fall generally within the 90-100% or the 0-10% bins; however
454 enough points (several thousand) are present in each intermediate tree den-
455 sity bin so that the inundation probabilities are robust and reliable, which
456 is also corroborated by the fact that the lines in Fig 8 are smooth rather
457 than randomly spiking through the transition zone. The sum of permanent
458 and transitory inundation probability for low vegetation (0-10% bin) is high
459 for both GIEMS-D3 and GSWO datasets, at 97% and 89%, respectively.
460 However, the distribution of permanent and transitory inundation is quite
461 different: 82% permanent and 15% transitory for GIEMS-D3, and 40% per-
462 manent and 49% transitory for GSWO. For the GSWO dataset, permanently
463 inundated pixels can be found only in the 0-10% bin while transitory pixels
464 decrease linearly from 50% to 0% with increasing tree cover. This behaviour
465 may, at least in part, be influenced by the thicker forest density in upland

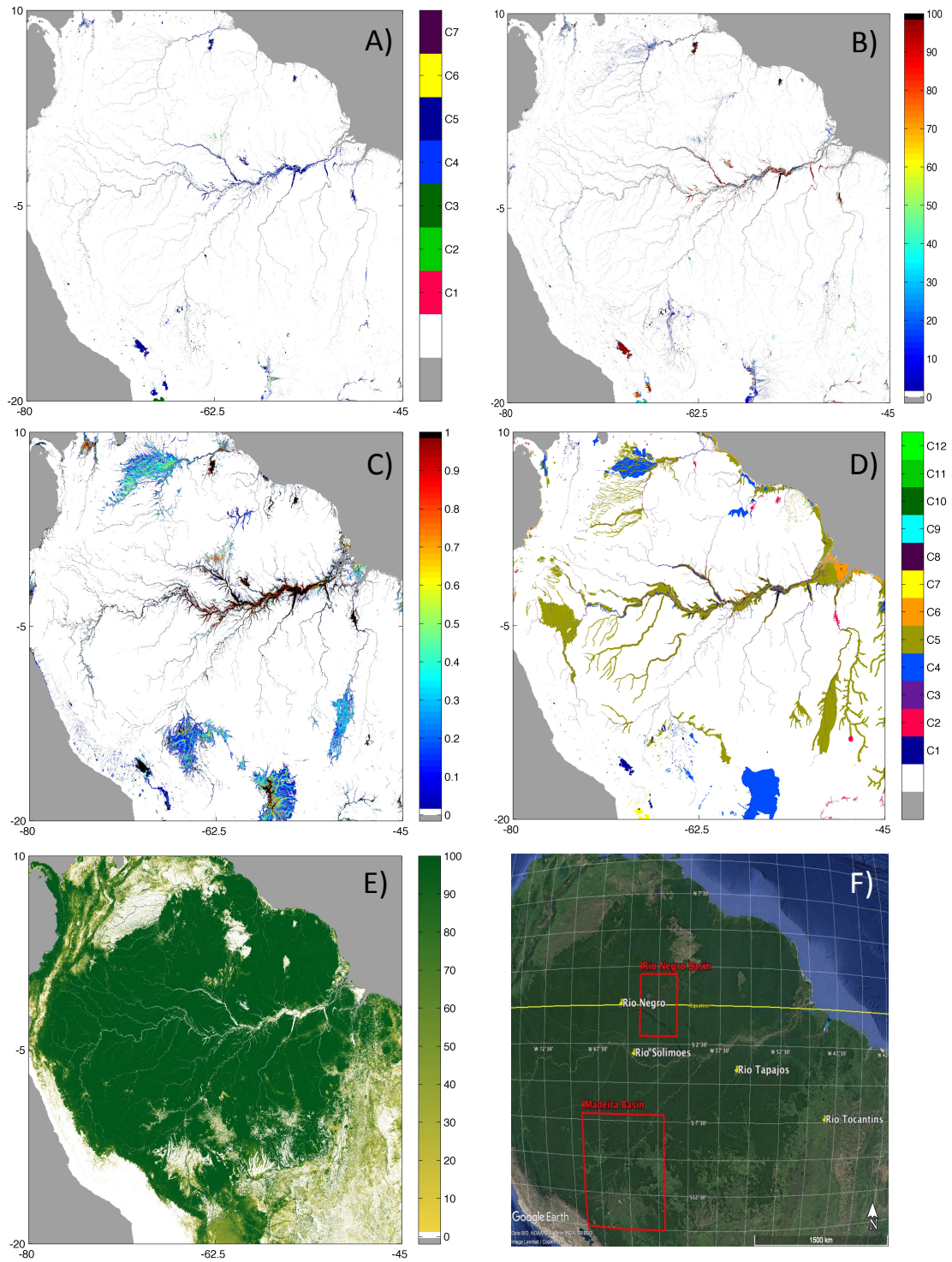


Figure 7: Comparison of the different surface water dataset over the Amazon: G3WBM (A), GSWO (B), GIEMS-D3 (C), GLWD (D), tree density from MODIS for interpretation (E), and indication of the two commented basins and four rivers (F). See Tab. 1 for the definition of the G3WBM and GLWD classes.

466 areas compounded with the limitations of Landsat detection.

467 For GIEMS-D3, the transitory inundation probability in tree density bins
468 is fairly constant from 10 to 90%, then experiences a steep decline in the 90-
469 100% bin. A peak occurs at 80-90% which might be related to the overesti-
470 mation of transitory inundation for water-saturated soils. With GIEMS-D3,
471 still 13% of transitory inundation is observed for the highest tree density bin,
472 confirming that flooding can be detected by GIEMS-D3 even under densely
vegetated areas.

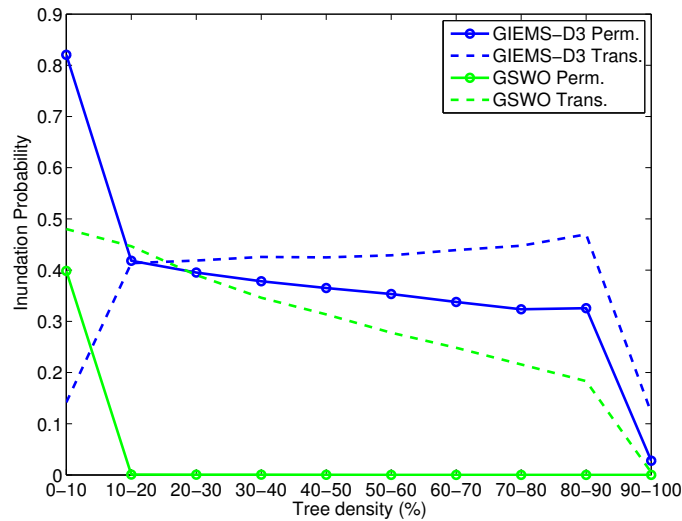
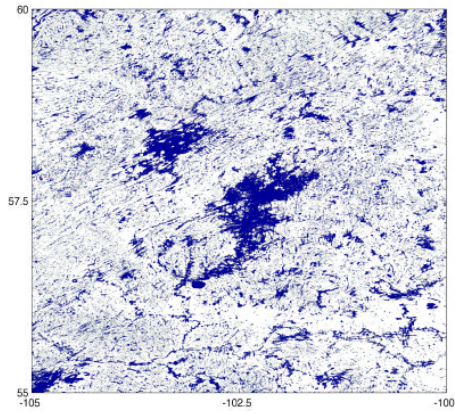


Figure 8: Probability of inundation for ten tree density ranges (0-10% to 90-100%), over a $5^\circ \times 5^\circ$ cell in the Amazon region (5°S - 0°S ; 70°W - 65°W). The probability of being inundated (permanently in continuous lines, or transitory in dashed lines) is estimated for each tree density bin, for GIEMS-D3 (blue) and GSWO (green).

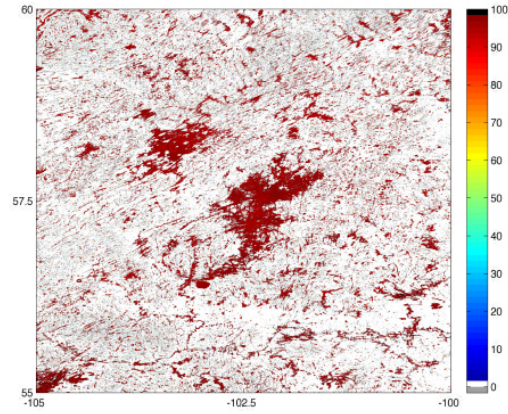
473

474 *4.2. Small water bodies at higher latitudes*

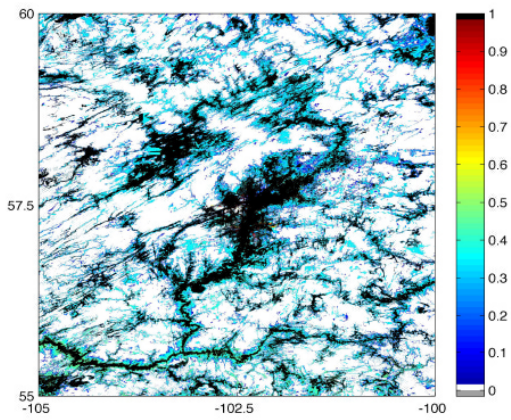
475 Fig. 9 illustrates the surface water estimates of the G3WBM, GSWO,
476 GIEMS-D3, and GLWD datasets over a high-latitude area (56°N - 60°N ; 105°W -
477 100°W) in Canada and supports that the larger hydrological features are very
478 similar from one dataset to another. The reference data of GLWD shows an
479 extensive homogeneous area of a wetland complex (classified as “25-50% wet-
480 land”), likely representing a generalised peatland region. This “biome class”
481 is not replicated in the other datasets that convey a water classification in-
482 formation. Landsat estimates (G3WBM and GSWO) show no transitory
483 surface waters but only permanent ones. This pattern is likely related to
484 an inundation definition issue or a time sampling problem causing confusion
485 with snow/ice cover, as inundation variation occurs during snowmelt periods
486 at these latitudes. Another possible explanation is also the presence of veg-
487 etation since Landsat cannot sense water beneath vegetation. On the other
488 hand, GIEMS-D3 shows a gradient of inundation probability, from the center
489 of the hydrological objects to the borders influenced likely by some confusion
490 with snow/ice cover and the limited ability to capture small lake features in
491 the landscape. The problem may be amplified by the downscaling scheme
492 relying on global-scale topographic and hydrographic information that is too
493 uncertain to adequately represent small variations in elevation within flat
494 regions. This regional case study over the northern latitudes highlights the
495 sampling issues in Landsat, and the difficulty for GIEMS-D3 to retrieve small
496 water bodies.



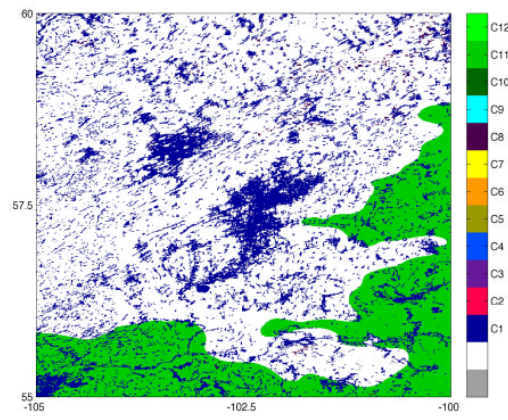
(a) G3WBM Classif.



(b) GSWO Occur.



(c) GIEMS-D3 Prob.



(d) GLWD Classif.

Figure 9: Inundation estimates from G3WBM (a), GSWO (b), GIEMS-D3 (c) and GLWD (d), over a $5^\circ \times 5^\circ$ cell in Canada. See Tab. 1 for the definition of the G3WBM and GLWD classes.

497 *4.3. The Ganges-Brahmaputra region and related cloud issues*

498 Characterising the distribution and variability of surface freshwater at
499 high resolution is critical for the Indian sub-continent and surrounding areas
500 where the availability of water resources is highly influenced by anthropogenic
501 pressure. Fig. 10 compares, over the Ganges-Brahmaputra River system
502 and the Bengal Delta, the various datasets. To support the interpretations,
503 Fig. 10 also shows tree density (E), the mean climatological cloud fraction
504 from MODIS in August over the region (F), the seasonality of the cloud cover
505 (G), and the number of months in which water is present during 2014 from
506 GSWO (H).

507 For reference, the GLWD map coarsely depicts three larger homogeneous
508 wetland areas classified as freshwater marsh and floodplains (C4), coastal
509 wetlands (C6), and 0-25% wetlands (C12). The three satellite-derived prod-
510 ucts agree in their representation of the permanent major rivers (Ganges-
511 Brahmaputra-Meghna River systems) and their large tributaries, as well as
512 some of the associated large inundated areas or wetlands of the Meghna River
513 and the Bengal Delta. However, this region is characterised by the presence
514 of complex areas with extensive transitory and seasonal flooding, which are
515 better captured by the more complete temporal coverage of GSWO com-
516 pared to G3WBM. For instance, the flooding region along the confluence
517 of the Ganges and the Kosi River in India as well as the floodplain of the
518 Meghna River are captured in GSWO, yet they are not visible in G3WBM.
519 The overall low coverage of surface water in both Landsat estimates is in high
520 contrast to GIEMS-D3 estimates, which are characterised by extensive and
521 in some cases overestimated flooded areas. The issue of overestimation in

522 the original GIEMS data over the Indian subcontinent has been discussed in
523 several publications (Papa et al., 2006, 2008, 2015; Salameh et al., 2017) and
524 while GIEMS is broadly able to capture the distributions and variations of
525 surface freshwater in the Ganges-Brahmaputra Basin, some analysis suggests
526 that the method encounters difficulties in accurately discriminating between
527 very saturated/moist soil and standing open water which can lead to poten-
528 tial overestimations of actual surface water extents, especially for saturated
529 soil in pixels with high flood coverage such as the delta region (Papa et al.,
530 2010).

531 Unlike in the Amazon Basin, low surface water detection in GSWO and
532 G3WBM over the Ganges-Brahmaputra region are not associated with dense
533 tree cover, see Fig. 10(E). On the other hand, Fig. 10(F) reveals that in
534 August the entire region is covered by clouds, in particular the areas around
535 the lower Ganges-Brahmaputra and delta which are covered by clouds for
536 90% of the month. August is also the month when excessive rainfall caused
537 by the South-West Indian monsoon produces maximum river discharge in the
538 Ganges-Brahmaputra system (Papa et al., 2012) along with associated large
539 flooding in the basin and in the lower delta. The persistent presence of cloud
540 cover during the monsoon season from May to September, see Fig. 10(G),
541 suggests that GSWO and G3WBM might encounter difficulties to properly
542 retrieve the maximum extent of inundation and seasonal surface water bodies
543 during their peak season. This might explain why GSWO detects most of
544 the surface water in April-May or October-December as shown in Fig. 10(G).

545

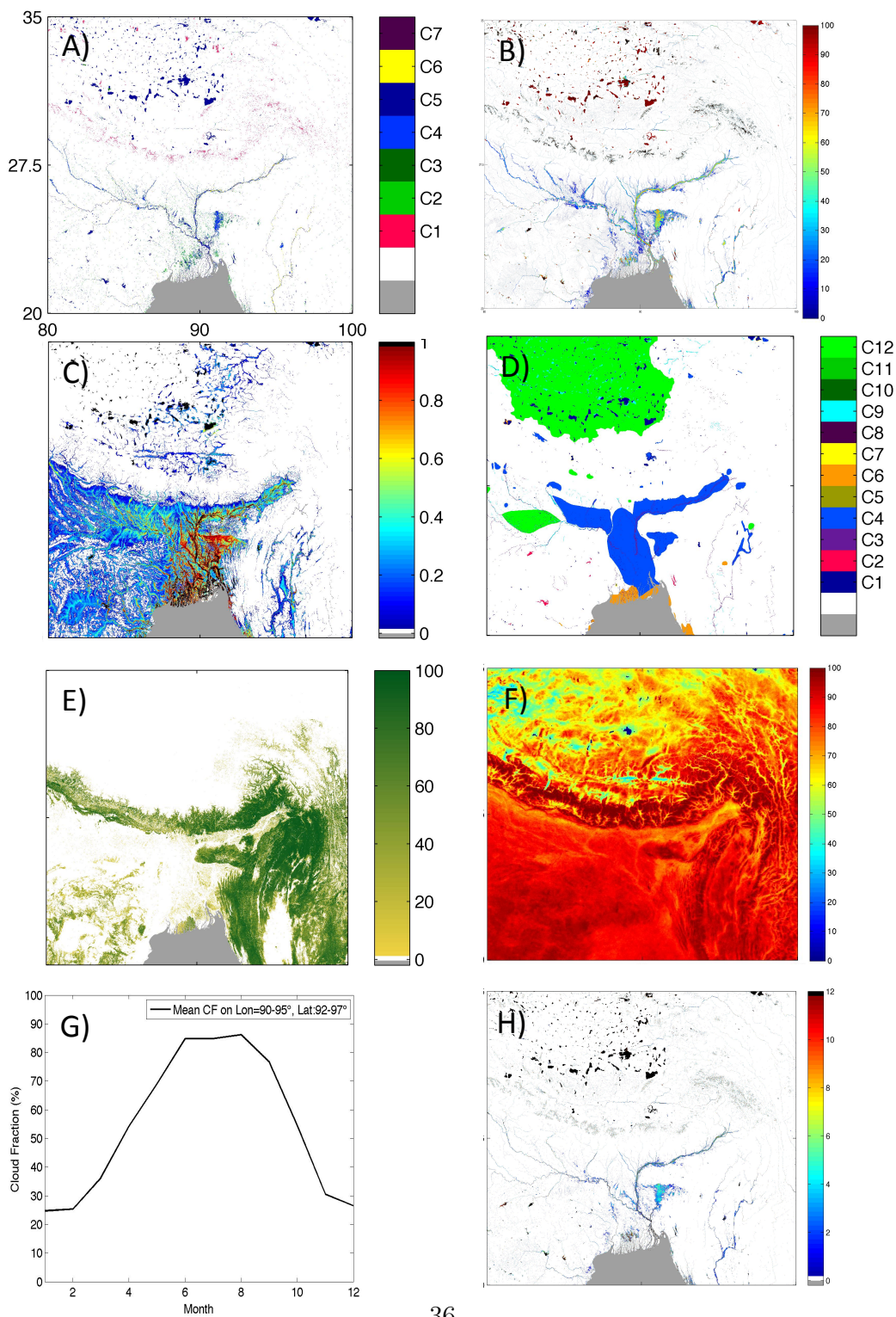


Figure 10: Comparison of surface water datasets for the Ganges-Brahmaputra region: G3WBM (A), GSWO (B), GIEMS-D3 (C), and GLWD (D). Tree density from MODIS (E), cloud fraction in August (F), seasonal cloud fraction (G) and GSWO season duration (in months) (H) are also represented for interpretation purposes. See Tab. 1 for the definition of G3WBM and GLWD classes.

546 **5. Conclusion and perspectives**

547 *5.1. Conclusion*

548 A comparison of Landsat-based (G3WBM and GSWO) and multi-satellite
549 (GIEMS-D3) datasets was conducted at global and regional scales to iden-
550 tify advantages and disadvantages in terms of detecting water surface areas
551 for both types of approaches. Overall, good agreement in permanent water
552 bodies was found for all datasets. Due to differences in observation methods,
553 discrepancies are apparent in particular for transitory (i.e. not permanently
554 inundated) zones. Landsat-based datasets have a very high nominal spatial
555 resolution and can detect even small water bodies at high accuracy, such as
556 those ubiquitous in northern latitudes. However, Landsat observations are
557 affected by cloud cover, snow/ice and vegetation. As a result, Landsat prod-
558 ucts are most apt at detecting open water bodies and variation within them,
559 but provide incomplete representation of seasonal wetlands or inundation
560 areas where the spectral signature is confounded by vegetation.

561 The multiple sensors behind GIEMS-D3 can penetrate vegetation and
562 clouds and are thus capable of retrieving non-open water wetland types and
563 of detecting temporal dynamics even if seasonal cloud cover is prevalent dur-
564 ing the periods of the year when inundation occurs. Current implementations
565 of the GIEMS-D3 downscaling method, however, have used topographic in-
566 formation which does not provide spatial accuracy comparable to direct ob-
567 servations from Landsat sensors. Furthermore, the current version of GIEMS
568 probably over-estimates inundation over water-saturated soils, and due to its
569 low nominal spatial resolution, it is not able to retrieve small water bodies.

570 SAR data (from ENVISAT, Sentinel and soon SWOT) would be a good

571 supplement because they warrant high-spatial resolution and are less sensi-
572 tive to clouds than the visible observations. However, long-term and global
573 mapping of surface waters has remained challenging due to localised param-
574 eterisation necessary for obtaining locally accurate maps. Regardless, SAR
575 remains among the most promising approaches for global baseline mapping of
576 inundation in vegetated areas, even if it cannot provide a long-term historic
577 time record such as available from GIEMS or Landsat.

578 In summary, the data sources compared possess complimentary strengths
579 which could be leveraged through assimilation and combination. The ex-
580 tensive archive of Landsat imagery provides reliable estimates of open water
581 bodies and variation, while downscaled GIEMS maps such as GIEMS-D3
582 provide a more complete, if less locally accurate, extent of inundation under
583 canopy and cloud cover.

584 *5.2. Perspectives*

585 In order to obtain the best estimate of global wetland extents at high
586 spatial resolution and with a long-term record, several ways forward should
587 be investigated which are listed in the following.

588

589 *Improvement of GIEMS and GIEMS-D3* - It was shown that GIEMS and
590 GIEMS-D3 have some good complementary information to Landsat observa-
591 tions. However, GIEMS and GIEMS-D3 also need to be further enhanced.
592 Three main ways are suggested to improve the original GIEMS dataset: (1)
593 The retrieval algorithm could be corrected to reduce the over-estimation of
594 inundated areas over saturated soils. (2) The temporal resolution could be
595 increased, from the monthly to a 10-day scale. (3) Most importantly, the time

596 record of GIEMS (currently 1993-2007) could be extended on both ends. The
597 time period covered by GIEMS is limited by auxiliary information (e.g. tem-
598 porally coherent surface temperatures, cloud flags) required for the GIEMS
599 retrievals, whereas the microwave observations are available for a longer pe-
600 riod (1972-present). This information was obtained from the ISCCP (In-
601 ternational Satellite Cloud Climatology Project)(Rossow and Schiffer, 1999).
602 Alternative ways could be investigated to perform the retrieval without these
603 auxiliary information, which would allow for building a GIEMS dataset from
604 1978 to present (about 40 years).

605 GIEMS-D3 could also be improved in several ways, for instance by using
606 a better downscaling scheme: (1) The floodability index used in the down-
607 scaling could be trained on Landsat data instead of GLWD. (2) A floodability
608 index could be developed with regional tuning adapted to different wetland
609 types (currently, the same model is used for arid, tropical, temperate or po-
610 lar areas) (Aires et al., 2017). (3) Other Digital Elevation Models (DEMs)
611 could be used instead of, or in combination with, SRTM/HydroSHEDS. For
612 instance, the newer version of SRTM at 30 m resolution could be tested.
613 New DEMs (Yamazaki et al., 2017) could also correct some artefacts such as
614 vegetation noise or tree height contamination (e.g., (Simard et al., 2011)).

615

616 *Data fusion of several sources of information* - Since both Landsat-based
617 data and GIEMS-D3 carry complementary information, it would be valuable
618 to combine them to obtain a better inundation product. There are several
619 avenues to achieve this: (1) The permanent water body area from Landsat
620 could be used to correct the minimum values of GIEMS-D3 which currently

621 tend to be underestimated due to the limited retrieval capability of GIEMS
622 in areas of low water fractions. (2) The Landsat occurrence could also replace
623 the topography-based floodability index that is used to perform the downscal-
624 ing of GIEMS-D3. In this way, an updated version of GIEMS-D3 would be
625 more compatible to Landsat products because it would follow similar spatial
626 patterns. The difficulty with of this approach is that the maximum GIEMS
627 inundation estimate is higher than that from Landsat, hence a Landsat-based
628 probability map is not covering the required extent. This shortcoming could
629 be solved by fusing the Landsat-based and topography-based probability in-
630 dices.

631 Aside from water and inundation masks, categorising surface water types
632 could benefit from developments of databases specific to discriminated wa-
633 terbody types. For instance, lakes and reservoirs (HydroLAKES) (Messenger
634 et al., 2016) or the Global River Widths from Landsat (GRWL) (Allen and
635 Pavelsky, 2015) could be used to improve downscaling of GIEMS or for post-
636 hoc classification efforts.

637

638 *Combination with SAR data* - Although global SAR coverage may eventually
639 provide the most comprehensive estimates of surface waters on its own, steps
640 improving global SAR retrieval would benefit from the use of GIEMS or
641 Landsat datasets. For instance, the GIEMS/Landsat estimates could help
642 in the development of a global SAR retrieval algorithm by serving either as
643 an *a priori* mask or as a first guess. GIEMS/Landsat combination would
644 also be a good tool to select the sites of validation campaigns for the SWOT
645 mission that will be launched in 2021 (Rodriguez, 2015; Prigent et al., 2016).

646 Finally, it could help in assessing the sensitivity of hydrological models to
647 this kind of high resolution data (e.g. assimilation experiments to estimate
648 river discharges), feed the SWOT simulator, or measure signal-to-noise ratio
649 constraints.

650 Arguably the most important reason for a continued improvement of sur-
651 face water datasets based on Landsat or multi-sensor products like GIEMS
652 is that they are our most promising tools to preserve the best possible in-
653 undation record of the past. Once reliable global SAR estimates become
654 available (from ENVISAT, Sentinel-1 or SWOT), they can be combined with
655 historic GIEMS/Landsat estimates to construct an instantaneous record of
656 inundation areas back to 1978, which then will be carried into the future by
657 the new and advanced SAR measurements.

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674 **References**

675 Aires, F., Miolane, L., Prigent, C., Pham, B., Fluet-Chouinard, E., Lehner,
676 B., Papa, F., 2017. A Global Dynamic Long-Term Inundation Ex-
677 tent Dataset at High Spatial Resolution Derived through Downscaling
678 of Satellite Observations. *Journal of Hydrometeorology* 18, 1305–1325.
679 URL: <http://journals.ametsoc.org/doi/10.1175/JHM-D-16-0155.1>,
680 doi:10.1175/JHM-D-16-0155.1.

681 Aires, F., Papa, F., Prigent, C., 2013. A Long-Term, High-Resolution
682 Wetland Dataset over the Amazon Basin, Downscaled from a Multi-
683 wavelength Retrieval Using SAR Data. *Journal of Hydrometeorology* 14,
684 594–607. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2013JHyMe..14..594A&link_type=EJOURNAL)
685 [query?bibcode=2013JHyMe..14..594A&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2013JHyMe..14..594A&link_type=EJOURNAL),
686 doi:10.1175/JHM-D-12-093.1.

687 Aires, F., Papa, F., Prigent, C., Crétaux, J.F., Bergé-Nguyen, M., 2014.
688 Characterization and Space–Time Downscaling of the Inundation Extent
689 over the Inner Niger Delta Using GIEMS and MODIS Data. *Journal of*
690 *Hydrometeorology* 15, 171–192. URL: [http://journals.ametsoc.org/](http://journals.ametsoc.org/doi/abs/10.1175/JHM-D-13-032.1)
691 [doi/abs/10.1175/JHM-D-13-032.1](http://journals.ametsoc.org/doi/abs/10.1175/JHM-D-13-032.1), doi:10.1175/JHM-D-13-032.1.

- 692 Allen, G.H., Pavelsky, T.M., 2015. Patterns of river width and sur-
693 face area revealed by the satellite-derived North American River Width
694 data set. *Geophysical Research Letters* 42, 395–402. URL: [http://](http://onlinelibrary.wiley.com/doi/10.1002/2014GL062764/full)
695 onlinelibrary.wiley.com/doi/10.1002/2014GL062764/full, doi:10.
696 1002/2014GL062764.
- 697 Biancamaria, S., Lettenmaier, D.P., Pavelsky, T.M., 2016. The SWOT Mis-
698 sion and Its Capabilities for Land Hydrology. *Surveys in Geophysics* 37,
699 307–337. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016SGeo...37..307B&link_type=EJOURNAL)
700 [query?bibcode=2016SGeo...37..307B&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016SGeo...37..307B&link_type=EJOURNAL),
701 doi:10.1007/s10712-015-9346-y.
- 702 Bousquet, P., Ciais, P., Miller, J.B., Dlugokencky, E.J., Hauglustaine, D.A.,
703 Prigent, C., Van der Werf, G.R., Peylin, P., Brunke, E.G., Carouge, C.,
704 Langenfelds, R.L., Lathière, J., Papa, F., Ramonet, M., Schmidt, M.,
705 Steele, L.P., Tyler, S.C., White, J., 2006. Contribution of anthropogenic
706 and natural sources to atmospheric methane variability. *Nature* 443, 439–
707 443. URL: <http://www.nature.com/doi/10.1038/nature05132>,
708 doi:10.1038/nature05132.
- 709 Chahine, M.T., 1992. The hydrological cycle and its influence on cli-
710 mate. *Nature* 359, 373–380. URL: [http://adsabs.harvard.edu/](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=1992Natur.359..373C&link_type=EJOURNAL)
711 [cgi-bin/nph-data_query?bibcode=1992Natur.359..373C&link_type=](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=1992Natur.359..373C&link_type=EJOURNAL)
712 [EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=1992Natur.359..373C&link_type=EJOURNAL), doi:10.1038/359373a0.
- 713 Crétaux, J.F., Abarca-del Río, R., Berge-Nguyen, M., Arsen, A.,
714 Drolon, V., Clos, G., Maisongrande, P., 2016. Lake Volume Moni-
715 toring from Space. *Surveys in Geophysics* 37, 269–305. URL: [http:](http://)

716 //adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016SGeo.
717 ..37..269C&link_type=EJOURNAL, doi:10.1007/s10712-016-9362-6.

718 Feng, M., Sexton, J.O., Channan, S., Townshend, J.R., 2014. A global,
719 high-resolution (30-m) inland water body dataset for 2000: first results
720 of a topographic-spectral classification algorithm. *International Journal*
721 *of Digital Earth* 9, 113–133. URL: [http://www.tandfonline.com/doi/](http://www.tandfonline.com/doi/full/10.1080/17538947.2015.1026420)
722 [full/10.1080/17538947.2015.1026420](http://www.tandfonline.com/doi/full/10.1080/17538947.2015.1026420), doi:10.1080/17538947.2015.
723 1026420.

724 Fluet-Chouinard, E., Lehner, B., Rebelo, L.M., Papa, F., Hamilton, S.K.,
725 2015. Development of a global inundation map at high spatial resolution
726 from topographic downscaling of coarse-scale remote sensing data. *Re-*
727 *mo*te Sensing of Environment 158, 348–361. URL: [http://linkinghub.](http://linkinghub.elsevier.com/retrieve/pii/S0034425714004258)
728 [elsevier.com/retrieve/pii/S0034425714004258](http://linkinghub.elsevier.com/retrieve/pii/S0034425714004258), doi:10.1016/j.rse.
729 2014.10.015.

730 Frappart, F., Papa, F., da Silva, J.S., Ramillien, G., Prigent, C.,
731 Seyler, F., Calmant, S., 2012. Surface freshwater storage and dynam-
732 ics in the Amazon basin during the 2005 exceptional drought. *Env-*
733 *iron. Res. Lett.* 7. URL: [http://stacks.iop.org/1748-9326/7/i=4/](http://stacks.iop.org/1748-9326/7/i=4/a=044010?key=crossref.366806a20b43202797338f61d0a23969)
734 [a=044010?key=crossref.366806a20b43202797338f61d0a23969](http://stacks.iop.org/1748-9326/7/i=4/a=044010?key=crossref.366806a20b43202797338f61d0a23969), doi:10.
735 1088/1748-9326/7/4/044010.

736 Getirana, A.C.V., Boone, A., Yamazaki, D., Decharme, B., Papa, F.,
737 Mognard, N., 2012. The Hydrological Modeling and Analysis Platform
738 (HyMAP): Evaluation in the Amazon Basin. *Journal of Hydrometeorology*
739 13, 1641–1665. URL: http://adsabs.harvard.edu/cgi-bin/nph-data_

740 query?bibcode=2012JHyMe..13.1641G&link_type=EJOURNAL,
741 doi:10.1175/JHM-D-12-021.1.

742 Gleick, P.H., 1989. Climate change, hydrology, and water resources. Re-
743 views of Geophysics 27, 329–344. URL: <http://doi.wiley.com/10.1029/RG027i003p00329>,
744 doi:10.1029/RG027i003p00329.

745 Hansen, M.C., DeFries, R.S., Townshend, J.R.G., Carroll, M., Dim-
746 iceli, C., Sohlberg, R.A., Hansen, M.C., DeFries, R.S., Town-
747 shend, J.R.G., Carroll, M., Dimiceli, C., Sohlberg, R.A., 2009.
748 Global Percent Tree Cover at a Spatial Resolution of 500 Meters:
749 First Results of the MODIS Vegetation Continuous Fields Algo-
750 rithm 7, 1–15. URL: [http://journals.ametsoc.org/doi/abs/](http://journals.ametsoc.org/doi/abs/10.1175/1087-3562(2003)007%3C0001%3AGPTCAA%3E2.0.CO%3B2)
751 [10.1175/1087-3562\(2003\)007%3C0001%3AGPTCAA%3E2.0.CO%3B2](http://journals.ametsoc.org/doi/abs/10.1175/1087-3562(2003)007%3C0001%3AGPTCAA%3E2.0.CO%3B2),
752 doi:10.1175/1087-3562(2003)007<0001:GPTCAA>2.0.CO;2.

753 Lehner, B., Döll, P., 2004. Development and validation of a global
754 database of lakes, reservoirs and wetlands. Journal of Hydrology 296,
755 1–22. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_query?](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2004JHyd..296....1L&link_type=EJOURNAL)
756 [bibcode=2004JHyd..296....1L&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2004JHyd..296....1L&link_type=EJOURNAL), doi:10.1016/j.
757 [jhydrol.2004.03.028](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2004JHyd..296....1L&link_type=EJOURNAL).

758 Lehner, B., Verdin, K., Jarvis, A., 2008. New global hydrography derived
759 from spaceborne elevation data. Eos, Transactions American Geophysical
760 Union 89, 93–94. URL: <http://doi.wiley.com/10.1029/eost2008E010>,
761 doi:10.1029/eost2008E010.

762 Messenger, M.L., Lehner, B., Grill, G., Nedeva, I., Schmitt, O.,

763 2016. Estimating the volume and age of water stored in global
764 lakes using a geo-statistical approach. Nature Communications 7,
765 13603. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016NatCo...713603M&link_type=EJOURNAL)
766 [query?bibcode=2016NatCo...713603M&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016NatCo...713603M&link_type=EJOURNAL),
767 doi:10.1038/ncomms13603.

768 Mueller, N., Lewis, A., Roberts, D., Ring, S., Melrose, R., Sixsmith,
769 J., Lymburner, L., McIntyre, A., Tan, P., Curnow, S., Ip, A., 2016.
770 Water observations from space: Mapping surface water from 25years
771 of Landsat imagery across Australia. Remote Sensing of Environment
772 174, 341–352. URL: <http://dx.doi.org/10.1016/j.rse.2015.11.003>,
773 doi:10.1016/j.rse.2015.11.003.

774 Nakaegawa, T., 2012. Comparison of Water-Related Land Cover Types in
775 Six 1-km Global Land Cover Datasets. Journal of Hydrometeorology 13,
776 649–664. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2012JHyMe..13..649N&link_type=EJOURNAL)
777 [query?bibcode=2012JHyMe..13..649N&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2012JHyMe..13..649N&link_type=EJOURNAL),
778 doi:10.1175/JHM-D-10-05036.1.

779 Papa, F., Bala, S.K., Pandey, R.K., Durand, F., Gopalakrishna,
780 V.V., Rahman, A., Rossow, W.B., 2012. Ganga-Brahmaputra
781 river discharge from Jason-2 radar altimetry: An update to the
782 long-term satellite-derived estimates of continental freshwater forc-
783 ing flux into the Bay of Bengal. J. Geophys. Res. Oceans 117,
784 C11021. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2012JGRC..11711021P&link_type=EJOURNAL)
785 [query?bibcode=2012JGRC..11711021P&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2012JGRC..11711021P&link_type=EJOURNAL),
786 doi:10.1029/2012JC008158.

- 787 Papa, F., Frappart, F., Güntner, A., Prigent, C., Aires, F., Getirana,
788 A.C.V., Maurer, R., 2013. Surface freshwater storage and variability
789 in the Amazon basin from multi-satellite observations, 1993–2007.
790 Journal of Geophysical Research: Atmospheres 118, 11,951–11,965.
791 URL: [http://onlinelibrary.wiley.com/doi/10.1002/2013JD020500/](http://onlinelibrary.wiley.com/doi/10.1002/2013JD020500/full)
792 full, doi:10.1002/2013JD020500.
- 793 Papa, F., Frappart, F., Malbeteau, Y., Shamsudduha, M., Vuruputur, V.,
794 Sekhar, M., Ramillien, G., Prigent, C., Aires, F., Pandey, R.K., Bala, S.,
795 Calmant, S., 2015. Satellite-derived surface and sub-surface water storage
796 in the Ganges–Brahmaputra River Basin. Journal of Hydrology: Regional
797 Studies 4, 15–35. URL: [http://dx.doi.org/10.1016/j.ejrh.2015.03.](http://dx.doi.org/10.1016/j.ejrh.2015.03.004)
798 004, doi:10.1016/j.ejrh.2015.03.004.
- 799 Papa, F., Guntner, A., Frappart, F., Prigent, C., Rossow, W.B., 2008. Vari-
800 ations of surface water extent and water storage in large river basins: A
801 comparison of different global data sources. Geophysical Research Let-
802 ters 35, L11401. URL: [http://doi.wiley.com/10.1029/2008GL033857,](http://doi.wiley.com/10.1029/2008GL033857)
803 doi:10.1029/2008GL033857.
- 804 Papa, F., Prigent, C., Aires, F., Jimenez, C., Rossow, W.B., Matthews, E.,
805 2010. Interannual variability of surface water extent at the global scale,
806 1993–2004. Journal of Geophysical Research: Atmospheres (1984–2012)
807 115. URL: [http://onlinelibrary.wiley.com.ezproxy.cul.columbia.](http://onlinelibrary.wiley.com.ezproxy.cul.columbia.edu/doi/10.1029/2009JD012674/full)
808 edu/doi/10.1029/2009JD012674/full, doi:10.1029/2009JD012674.
- 809 Papa, F., Prigent, C., Rossow, W.B., 2006. Inundated wetland dynamics
810 over boreal regions from remote sensing: The use of Topex-Poseidon dual-

811 frequency radar altimeter observations 27, 4847–4866. URL: <http://www.tandfonline.com/doi/abs/10.1080/01431160600675887>, doi:10.1080/
812 01431160600675887.
813

814 Pekel, J.F., Cottam, A., Gorelick, N., Belward, A.S., 2016. High-resolution
815 mapping of global surface water and its long-term changes. *Nature* 540,
816 418–422. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016Natur.540..418P&link_type=EJOURNAL)
817 [query?bibcode=2016Natur.540..418P&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016Natur.540..418P&link_type=EJOURNAL),
818 doi:10.1038/nature20584.

819 Pham-Duc, B., Prigent, C., Aires, F., 2017. Surface Water Monitoring within
820 Cambodia and the Vietnamese Mekong Delta over a Year, with Sentinel-
821 1 SAR Observations. *Water* 9, 366–21. URL: [http://www.mdpi.com/](http://www.mdpi.com/2073-4441/9/6/366)
822 [2073-4441/9/6/366](http://www.mdpi.com/2073-4441/9/6/366), doi:10.3390/w9060366.

823 Prigent, C., Lettenmaier, D.P., Aires, F., Papa, F., 2016. Toward
824 a High-Resolution Monitoring of Continental Surface Water Extent
825 and Dynamics, at Global Scale: from GIEMS (Global Inunda-
826 tion Extent from Multi-Satellites) to SWOT (Surface Water Ocean
827 Topography). *Surveys in Geophysics* 37, 339–355. URL: [http://](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016SGeo..37..339P&link_type=EJOURNAL)
828 [adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016SGeo.](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016SGeo..37..339P&link_type=EJOURNAL)
829 [..37..339P&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2016SGeo..37..339P&link_type=EJOURNAL), doi:10.1007/s10712-015-9339-x.

830 Prigent, C., Matthews, E., Aires, F., Rossow, W.B., 2001. Remote sensing
831 of global wetland dynamics with multiple satellite data sets. *Geophysical*
832 *Research Letters* 28, 4631–4634. URL: [http://adsabs.harvard.edu/](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2001GeoRL..28.4631P&link_type=EJOURNAL)
833 [cgi-bin/nph-data_query?bibcode=2001GeoRL..28.4631P&link_type=](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2001GeoRL..28.4631P&link_type=EJOURNAL)
834 [EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2001GeoRL..28.4631P&link_type=EJOURNAL), doi:10.1029/2001GL013263.

- 835 Prigent, C., Papa, F., Aires, F., Jimenez, C., Rossow, W.B., Matthews,
836 E., 2012. Changes in land surface water dynamics since the 1990s
837 and relation to population pressure. *Geophysical Research Letters* 39,
838 L08403. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2012GeoRL..39.8403P&link_type=EJOURNAL)
839 [query?bibcode=2012GeoRL..39.8403P&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2012GeoRL..39.8403P&link_type=EJOURNAL),
840 doi:10.1029/2012GL051276.
- 841 Prigent, C., Papa, F., Aires, F., Rossow, W.B., Matthews, E., 2007.
842 Global inundation dynamics inferred from multiple satellite observations,
843 1993–2000. *Journal of Geophysical Research: Atmospheres* (1984–2012)
844 112. URL: [http://onlinelibrary.wiley.com/ezproxy.cul.columbia.](http://onlinelibrary.wiley.com/ezproxy.cul.columbia.edu/doi/10.1029/2006JD007847/full)
845 [edu/doi/10.1029/2006JD007847/full](http://onlinelibrary.wiley.com/ezproxy.cul.columbia.edu/doi/10.1029/2006JD007847/full), doi:10.1029/2006JD007847.
- 846 Rodriguez, E., 2015. Surface Water and Ocean Topography Mission (SWOT).
847 Technical Report JPL D-61923. NASA JPL.
- 848 Rossow, W.B., Schiffer, R.A., 1999. Advances in understanding clouds from
849 ISCCP. *Bull. Amer. Meteor. Soc.* 80, 2261–2287.
- 850 Sakamoto, T., Van Nguyen, N., Kotera, A., Ohno, H., Ishitsuka, N.,
851 Yokozawa, M., 2007. Detecting temporal changes in the extent of an-
852 nual flooding within the Cambodia and the Vietnamese Mekong Delta
853 from MODIS time-series imagery. *Remote Sensing of Environment*
854 109, 295–313. URL: [http://linkinghub.elsevier.com/retrieve/pii/](http://linkinghub.elsevier.com/retrieve/pii/S0034425707000466)
855 [S0034425707000466](http://linkinghub.elsevier.com/retrieve/pii/S0034425707000466), doi:10.1016/j.rse.2007.01.011.
- 856 Salameh, E., Frappart, F., Papa, F., Güntner, A., Venugopal, V., Geti-
857 rana, A., Prigent, C., Aires, F., Labat, D., Laignel, B., 2017. Fifteen

858 Years (1993–2007) of Surface Freshwater Storage Variability in the Ganges-
859 Brahmaputra River Basin Using Multi-Satellite Observations. *Water* 9,
860 245–19. URL: <http://www.mdpi.com/2073-4441/9/4/245>, doi:10.3390/
861 w9040245.

862 Santoro, M., Wegmüller, U., Askne, J.I.H., 2010. Signatures
863 of ERS-Envisat Interferometric SAR Coherence and Phase of
864 Short Vegetation: An Analysis in the Case of Maize Fields.
865 *IEEE Transactions on Geoscience and Remote Sensing* 48, 1702–
866 1713. URL: [http://adsabs.harvard.edu/cgi-bin/nph-data_](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2010ITGRS..48.1702S&link_type=EJOURNAL)
867 [query?bibcode=2010ITGRS..48.1702S&link_type=EJOURNAL](http://adsabs.harvard.edu/cgi-bin/nph-data_query?bibcode=2010ITGRS..48.1702S&link_type=EJOURNAL),
868 doi:10.1109/TGRS.2009.2034257.

869 Simard, M., Pinto, N., Fisher, J.B., Baccini, A., 2011. Mapping forest canopy
870 height globally with spaceborne lidar. *J. Geophys. Res.* 116, G04021–
871 12. URL: <http://doi.wiley.com/10.1029/2011JG001708>, doi:10.1029/
872 2011JG001708.

873 Tulbure, M.G., Broich, M., Stehman, S.V., Kommareddy, A., 2016. Surface
874 water extent dynamics from three decades of seasonally continuous Landsat
875 time series at subcontinental scale in a semi-arid region. *Remote Sensing*
876 *of Environment* 178, 142–157. URL: [http://linkinghub.elsevier.com/](http://linkinghub.elsevier.com/retrieve/pii/S0034425716300621)
877 [retrieve/pii/S0034425716300621](http://linkinghub.elsevier.com/retrieve/pii/S0034425716300621), doi:10.1016/j.rse.2016.02.034.

878 Verpoorter, C., Kutser, T., Seekell, D.A., Tranvik, L.J., 2014. A global inven-
879 tory of lakes based on high-resolution satellite imagery. *Geophys. Res. Lett.*
880 41, 6396–6402. URL: <http://doi.wiley.com/10.1002/2014GL060641>,
881 doi:10.1002/2014GL060641.

- 882 Westerhoff, R.S., Kleuskens, M.P.H., Winsemius, H.C., Huizinga, H.J., Brak-
883 enridge, G.R., Bishop, C., 2013. Automated global water mapping based
884 on wide-swath orbital synthetic-aperture radar. *Hydrol. Earth Syst. Sci.*
885 17, 651–663. URL: [http://www.hydrol-earth-syst-sci.net/17/651/](http://www.hydrol-earth-syst-sci.net/17/651/2013/)
886 2013/, doi:10.5194/hess-17-651-2013.
- 887 Wilson, A.M., Jetz, W., 2016. Remotely Sensed High-Resolution Global
888 Cloud Dynamics for Predicting Ecosystem and Biodiversity Distributions.
889 *PLoS Biol* 14, 1–20. URL: [http://dx.plos.org/10.1371/journal.](http://dx.plos.org/10.1371/journal.pbio.1002415)
890 [pbio.1002415](http://dx.plos.org/10.1371/journal.pbio.1002415), doi:10.1371/journal.pbio.1002415.
- 891 Winsemius, H., Jongman, B., Veldkamp, T., Hallegatte, S., Bangalore, M.,
892 Ward, P., 2015. Disaster risk and poverty: assessing the global exposure
893 of the poor to floods and droughts. *EGU General Assembly 2015* 17, 3225.
894 URL: <http://adsabs.harvard.edu/abs/2015EGUGA..17.3225W>.
- 895 Yamazaki, D., Ikeshima, D., Tawatari, R., Yamaguchi, T., O’Loughlin,
896 F., Neal, J.C., Sampson, C.C., Kanae, S., Bates, P.D., 2017. A high-
897 accuracy map of global terrain elevations. *Geophys. Res. Lett.* 44, 5844–
898 5853. URL: <http://doi.wiley.com/10.1002/2017GL072874>, doi:10.
899 1002/2017GL072874.
- 900 Yamazaki, D., Trigg, M.A., Ikeshima, D., 2015. Development of a global
901 ~90m water body map using multi-temporal Landsat images. *Re-*
902 *mote Sensing of Environment* 171, 337–351. URL: [http://linkinghub.](http://linkinghub.elsevier.com/retrieve/pii/S0034425715301656)
903 [elsevier.com/retrieve/pii/S0034425715301656](http://linkinghub.elsevier.com/retrieve/pii/S0034425715301656), doi:10.1016/j.rse.
904 2015.10.014.