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1 Estimation of river flow using CubeSats remote sensing

2
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16 **Abstract:**

17
18 River flow characterizes the integrated response from watersheds, so it is essential to quantify to
19 understand the changing water cycle and underpin the sustainable management of freshwaters.
20 However, river gauging stations are in decline with ground-based observation networks shrinking.
21 This study proposes a novel approach of estimating river flows using the Planet CubeSats
22 constellation with the possibility to monitor on a daily basis at the sub-catchment scale through
23 remote sensing. The methodology relates the river discharge to the water area that is extracted
24 from the satellite image analysis. As a testbed, a series of Surface Reflectance PlanetScope images
25 and observed streamflow data in Araguaia River (Brazil) were selected to develop and validate
26 the methodology. The study involved the following steps: (1) survey of measurements of water
27 level and river discharge using in-situ data from gauge-based Conventional Station (CS) and
28 measurements of altimetry using remote data from JASON-2 Virtual Station (JVS); (2) survey of

29 Planet CubeSat images for dates in step 1 and without cloud cover; (3) image preparation
30 including clipping based on different buffer areas and calculation of the Normalized Difference
31 Vegetation Index (NDVI) per image; (4) water bodies areas calculation inside buffers in the Planet
32 CubeSat images; and (5) correlation analysis of CubeSat water bodies areas with JVS and CS
33 data. Significant correlations between the water bodies areas with JVS ($R^2 = 88.83\%$) and CS (R^2
34 $= 96.49\%$) were found, indicating that CubeSat images can be used as a CubeSat Virtual Station
35 (CVS) to estimate the river flow. This newly proposed methodology using CubeSats allows for
36 more accurate results than the JVS-based method used by the Brazilian National Water Agency
37 (ANA) at present. Moreover, CVS requires small areas of remote sensing data to estimate with
38 high accuracy the river flow and the height variation of the water in different timeframes. This
39 method can be used to monitor sub-basin scale discharge and to improve water management,
40 particularly in developing countries where the presence of conventional stations is often very
41 limited.

42

43 **Highlights:**

44

- 45 • Use of remote sensing information from Planet CubeSats constellation to build and assess a
46 methodology to river flow estimation;
- 47 • This method has significant opportunity for river flow estimation at ungauged sites at the daily
48 and sub-basin scales;
- 49 • The improvement of river flow measurements is essential to understand the changing water
50 cycle and underpin the sustainable management of freshwaters.

51

52 **Keywords:** River flow; CubeSat; Remote Sensing; Cerrado (Savannah); Change Detection;
53 Spatiotemporal Resolution.

54

55

56 **1 Introduction**

57

58 Freshwater is a basic requirement for life but the knowledge of river flow rates is scarce
59 (Gleason and Smith, 2014). A better understanding of the large-scale water cycle process is
60 essential to underpin socio-economic development and sustainably manage water-dependent
61 ecosystems (Döll et al., 2014; Hannah et al., 2011; Kingston et al., 2020). River flow characterizes
62 the integrated hydrological response and water yield from watersheds. Nowadays, there is a clear
63 decline of river gauging stations and a shrinking of ground-based observation networks (Dixon et
64 al., 2020; Hannah et al., 2011).

65 Conventional gauging stations are well developed and have contributed to quantify the
66 movement of water in river channels. However, conventional stations are not enough to determine
67 more complex riverine environments that involve the movement of water over wetlands and
68 floodplains in multiple channel types (Lettenmaier, 2007), requiring new multidisciplinary
69 approaches to improve the observation networks.

70 The advances in remote sensing hydrology, particularly over the past 10 years, have
71 demonstrated that hydraulic variables can be measured reliably from orbiting satellite platforms
72 (Huang et al., 2018). As the deluge of big data continues to impact practically every commercial
73 and scientific domain, geosciences have also witnessed a major revolution from being a data-poor
74 field to a data-rich field (Karpatne et al., 2019; Reichstein et al., 2019). The use of remote sensing
75 by satellite for streamflow analyses can be categorized into techniques based on satellite altimetry,
76 Synthetic Aperture Radar (SAR), and optical images (Ahmad and Kim, 2019).

77 To accurately detect river flow regimes at a field scale from space, a new high spatial and
78 temporal resolution remote sensing source is necessary to improve water- level time series
79 (Bogning et al., 2018). While satellites such as Sentinel-2 and Landsat may have an adequate
80 spatial resolution for different applications (Sadeh et al., 2019), their temporal resolution (5 and
81 16 days revisit time, respectively) is not ideal for detection of flow regimes changes, as there may
82 be weeks between the acquisition of two clear-sky images (Houborg and McCabe, 2018a).

83 Applications of satellite remote sensing in hydrological surface water modelling, mapping,
84 and parameter estimation were reported in some reviews based on Earth Observing Systems
85 (Huang et al., 2018; Joshi et al., 2016; Musa et al., 2015; Wagner et al., 2018) mainly using SAR,
86 optical, altimetry and DEM data. Focusing flow river estimation, different techniques were
87 applied to estimate the river width by averaging multiple cross-sections over an area (Gleason
88 and Smith, 2014), use the Synthetic Aperture Radar (SAR) to calculate water area (Ahmad and
89 Kim, 2019), and fusion topography dataset (Anh and Aires, 2019; Moramarco et al., 2019). The
90 spatiotemporal restrictions for using remote sensing satellite data have been partly overcome via
91 multisensor data fusion (Houborg and McCabe, 2018b) but all solutions proposed can not be
92 replicated for daily measurements at a high spatial resolution.

93 Thus, remote sensing has the potential of conducting rapid, cost-effective, and continuous
94 surveys of river management practices over large scales. Notably, the constellations of micro or
95 nano-satellites, known as CubeSats, are revolutionizing the high spatiotemporal resolution
96 possibilities in remote sensing and can potentially be used to capture many observations over time
97 (Sadeh et al., 2019) and monitor dynamics surface water changes (Cooley et al., 2019, 2017). The
98 repetitive observation mechanism of multiples CubeSats enables studying the river dynamics and
99 observe different physical properties (Marinho et al., 2020). Among the different Cubesats on orbit,
100 the CubeSat constellation provided by Planet Labs Inc. has the advantage of providing a near-
101 daily revisit time globally at 3-meter orthorectified spatial resolution. It is also worth noting that
102 Remote Sensing (RS) has several methods and techniques to identify land and water areas
103 considering bands variation of different multi-spectral images (Acharya et al., 2018). Index
104 methods are mostly used to estimate surface water that separates the water from the background
105 based on a threshold value. Among these indexes, Normalized Difference Vegetation Index
106 (NDVI) and Normalized Difference Water Index (NDWI) are frequently adopted as they include
107 visible and Near Infrared (NIR) bands provided by satellite optical images (Elsahabi et al., 2016).

108 The aims of this study were (1) to develop an innovative methodology for semi-automated
109 river flow estimation using visible and NIR from Planet CubeSats bands to detect changes in the
110 surface of flood area and (2) to compare Planet CubeSats derived river flow with Conventional

111 flow meters Station (CS) and JASON (Joint Altimetry Satellite Oceanography Network) Virtual
112 gauging Station (JVS). The Araguaia River, in the Cerrado biome of Brazil, was selected as the
113 research area.

114

115 **2. Description of the study area**

116

117 The Tocantins-Araguaia hydrographic region, with a total area of 920,087 km² and 13,779
118 m³/s of average discharge (Brasil/ANA, 2015), is the most important fluvial system draining the
119 tropical savannah ecoregion of Brazil (Cerrado biome). Some areas of this region have been
120 affected by severe water scarcity events since 2012 (Naturatins, 2017). In general terms, the
121 hydrologic regime depends on the dominant climate (tropical wet-dry) with floods from January
122 to May (rain period) and low water between June to September. This region is the confluence of
123 two major rivers: the Tocantins River (~1,960 km extension) and the Araguaia River (~2,600 km
124 extension). The Araguaia sub-basin (around 386,765 km²) represents around 42% of the
125 hydrographic region and along its path, is placed the largest river island in the world, Bananal
126 Island (Figure 1).

127

128 *Figure 1*

129

130 The Araguaia River is one of the priority areas for conservation of the aquatic biodiversity of
131 the Cerrado biome and has been the target of political and environmental debates due to the
132 intense and indiscriminate expansion of agricultural activities, with a greater degradation of the
133 natural environment during the last four decades (Latrubesse and Stevaux, 2006). The entire sub-
134 basin has just 166 conventional river gauging stations for an area of 386,765 km² and more than
135 6,000 river stretches mapped.

136 This region needs to be better monitored due to the increase in intensive agriculture and the
137 use of water (Althoff et al., 2020). Especially in the Araguaia River, the irrigated area increased

138 more than 116% between 2006 and 2012, and the cultivated area increased by about 20% in the
139 same period (ANA, 2015). In the last decade, the Araguaia sub-basin has been suffering from
140 water scarcity in several tributaries of the Araguaia river, obliging managers to take actions for
141 rationing the water use in agriculture to prioritize human and animal supply (Lauris, 2019;
142 Naturatins, 2017).

143 As a testbed to develop and validate the proposed methodology, two river gauging stations
144 that are calibrated by ANA and used as an official instrument for public policies in this region
145 were selected. One of the rivers gauging stations was the in-situ Conventional Station (CS) ID
146 26350000 (<http://gestorpcd.ana.gov.br>) managed by ANA, located in São Felix do Araguaia –
147 MT (11°37'8.6" S; 50°39'75.0" W – WGS84 Datum). This station employs an instrument for
148 monitoring the river flow for 24/7 hours with records registered every 15 minutes. The other river
149 gauging station was the JASON-2 Virtual Station (JVS) ID 1055S05036WO
150 (<http://hidrosat.ana.gov.br>), which is monitored by ANA in cooperation with Institut de
151 Recherche pour le Développement (IRD) with barycenter data at 10°54'42.0" S; 50°36'48.6" W
152 – WGS84 Datum. This station acquires altimetry information by satellite to monitor the water
153 level and derived river flow, with no equipment locally installed. The JVS dataset is related to the
154 average altitude of all available altimetry data, along the JASON-2 track, over the river area in
155 each satellite cycle. JVS observations occur every 9.9 days from the JASON-2 satellite in the
156 same ground track within a margin of ± 1 km (CNES; NASA, 2011).

157 The detailed characteristics of both selected stations are shown in Figure 2. The distance
158 between the CS and JVS is relatively close with 78 km (Euclidean distance) allowing their
159 comparison with the proposed methodology.

160

161

Figure 2

162

163

164 3. Data and Methods

165
166 For this study, the available Planet CubeSat data was explored to establish an innovative
167 method for estimating river flow based on daily remote sensing images.

168 169 3.1. CubeSat data

170
171 This study used Planet images to develop a flow estimation model. These images are captured
172 by Planet using an approach based on ‘fast design’ to launch satellites, mission control and
173 operations systems, and the development of a web-based platform for imagery processing and
174 delivery (www.planet.com). Planet is a commercial satellite operator that enhanced observation
175 capacity offered by constellations of small and standardized satellites and employs an “always-
176 on” image-capturing method (Planet Team, 2020).

177 This CubeSat constellation consists of 130 small-satellites at an altitude of approximately 475
178 km, following each other on two near-polar orbits of roughly 8° (descendent orbit) and 98°
179 (ascendent orbit) inclination respectively, imaging the Earth at local morning time (Planet Team,
180 2020). The distance along the orbit between the CubeSats is constructed such that the longitudinal
181 progression between them over the rotating Earth leads to the scan of the surface. Thus, the full
182 constellation provides daily sun-synchronous coverage of the entire Earth (except the polar hole)
183 with the resolution of 3.7 meters at nadir (Ground Sample Distance), 12-bit radiometric
184 resolution, and 4 spectral bands (Blue [455 - 515 nm], Green [500 - 590 nm], Red [590 - 670 nm]
185 and Near-InfraRed [780 - 860 nm]) (Planet Team, 2020).

186 The CubeSat across-track off-nadir viewing angle used for imaging usually to be lower than
187 5° (Planet Team, 2020) reducing the complexity to evaluate bands’ variation of different multi-
188 spectral images arising from environmental noise such as shadow, however, these CubeSat do not
189 present some spectral bands as Middle Infrared (MIR) and Shortwave Infrared (SWIR), used in
190 different indexes applied to water such as TCW, MNDWI, NDWI, AWEI (Elsahabi et al., 2016).

191 The images can be downloaded from the Planet portal (<https://www.planet.com/explorer>) and
192 include three types of raster images: (a) digital number (DN) commonly represented by an
193 uncalibrated image into physically meaningful units; (b) top of atmosphere reflectance (TOA)
194 that is the reflectance measured by a space-based sensor flying higher than the earth's atmosphere
195 (calibrated to a radiance image), and (c) surface reflectance (SR) that is the radiance image
196 atmospherically corrected and ready to be used to extract quantitative information about features
197 on the Earth surface. As SR reflects the difference among land covers more accurately than other
198 remotely sensed measurements (Huang et al., 2018). In this study, it was used the SR image
199 products, orthorectified with 3 meters spatial resolution, positional accuracy with less than 10-
200 meters Root Mean Square Error (RMSE) suitable for analytic and visual applications.

201

202 *3.2. A method for estimating river flows using CubeSats*

203

204 This study was divided into five steps: (1) survey of measurements of water level and
205 river discharge using in-situ data from gauge-based Conventional Station (CS) and measurements
206 of altimetry using remote data from JASON-2 Virtual Station (JVS); (2) preparation of river
207 section and buffers and survey of CubeSat images for selected dates (correlated with step 1 and
208 without cloud cover); (3) image preparation, including clipping based on different buffer areas
209 followed by NDVI calculation per image, and data processing over CS and JVS stations using
210 Extract-Transform-Load (ETL); (4) water bodies areas calculation inside buffer for river flow
211 estimation in the Planet CubeSat images; and (5) correlation analysis of CubeSat water bodies
212 areas with JVS and CS data (Figure 3).

213

214

Figure 3

215

216 Firstly, the CS and JVS measurements were collected in the period of 01/01/2018 to
217 30/07/2018, a period that historically includes the greatest variation in the flow of this river over
218 the years. The dataset for CS included the water level and river flow every 15 minutes. The JVS

219 were collected altimetry data in repetitive periods of 10 days according to the measures provided
220 by the altimetry missions satellite. The use of JVS data was independent of the time of collection
221 and resulted in a median of 11:03 a.m. local time.

222 In the second step, a cross-section of the river was used as a reference for creating side buffers
223 with 50, 250, 500, and 1000 meters. This cross-section was determined nearby to the JASON's
224 tracking to provide better conditions of comparison between the virtual stations and these buffers
225 sections were created to reduce the satellite image processing area in the water surface calculation.
226 Using the location of these buffers, Planet CubeSat images were searched for all dates with JVS
227 data. The CubeSat images search also included the completed cover of buffer areas, the absence
228 of clouds, and the possibility of using the surface reflectance product (SR) as input (Table 1).

229 In the third step, each image downloaded from the Planet portal was clipped on the buffer
230 areas and processed to calculate the Normalized Difference Vegetation Index (NDVI) with a scale
231 ranging from -1 to 1. The NDVI was calculated using the Red and Near-InfraRed regions of the
232 electromagnetic spectrum with Equation 1 since these satellites do not have yet more specific
233 spectral bands for the development of more sophisticated methods. For each image analyzed, the
234 river flood areas were classified with NDVI values lower than 0.15.

235

$$236 \quad NDVI = \frac{(NIR\ Band - Red\ Band)}{(NIR\ Band + Red\ Band)} \quad (1)$$

237

238 In the fourth step, the water bodies' areas were calculated for all clipped buffers in the dates
239 analyzed, resulting in a temporal table of flooding areas. Then, in the fifth step, we performed the
240 regression curves (exponential, linear, logarithmic, polynomial, power-law, and moving
241 averages) between the water bodies areas for 4 different buffers (50, 250, 500, and 1000 m) and
242 the 3 sets of reference data (JVS - altimetry, CS - water level, CS - flow). After that, 12 different
243 Pearson coefficients (R^2) were determined according to the best-fitted regression curves. The
244 relationship between R^2 and the four buffer areas were analyzed for each set of reference data,

245 determining the equation used to predict the river flow from the CubeSat image flood area, which
246 represented the CubeSat Virtual Station (CVS).

247

248 **4 Results**

249

250 The data collected from CS showed a river flow ranging from 868 to 4,739 m³/s and a water
251 level varying from 328 to 710 cm for the entire monitoring period in the Araguaia basin. A
252 significant relationship between the river flow and the water level measurements ($R^2=1$) was
253 found (Figure 4a). Concerning the JVS data, altimetry values between 177.9 to 181.1 m were
254 observed, with a good correlation to CS water level ($R^2= 0.85$) (Figure 4b).

255

256 *Figure 4*

257

258 In the survey of Planet CubeSat images, 8 image dates were selected with CS and JVS
259 correspondent data, completed cover the buffer areas, absence of clouds, and available surface
260 reflectance product (SR) (Table 1).

261

262 *Table 1*

263

264 In these 8 images, water bodies areas ranging from 39,924 to 54,846 m² for buffer 50 m, from
265 173,313 to 276,984 m² for buffer 250 m, from 320,805 to 557,586 m² for buffer 500 m, and from
266 563,895 to 1,097,469 m² for buffer 1000 m were determined (Table 2). Considering the maximum
267 values of water bodies in each buffer, it was verified that the flood area corresponds to 77.3%,
268 63.9%, 52.5%, and 37.7%, respectively, for the 50 m, 250 m, 500 m, and 1000 m buffer areas.

269

270 *Table 2*

271

272 Based on the water bodies areas determined in each buffer area, the regression models were
273 performed as demonstrated in Figure 5. Due to the obtained data values and its measure of
274 greatness, the river flow equation was adjusted to the power-law regression model, while the
275 water level and altimetry equations were adjusted to linear regression models.

276

277 *Figure 5*

278

279 Considering the results obtained in the regression models, it was found that the buffer of 500
280 m was the lowest buffer area capable of providing a high Pearson's coefficient that remained
281 stable even with the increase of buffer area (Figure 6). Therefore, the buffer of 500 m was selected
282 to be the CVS and to estimate the river flow.

283

284 *Figure 6*

285

286 To estimate the river flow (Q_e), water level (L_e) and altimetry (A_e) were determined the
287 Equations 2 ($R^2 = 96.49\%$), 3 ($R^2 = 94.38\%$) and 4 ($R^2 = 88.83\%$) respectively; in which A_{f500r}
288 is the flooding area (m^2) in the 500 m buffer.

289

$$290 \quad Q_e = 10^{-13} \cdot A_{f500r}^{2.8737} \quad (2)$$

291

$$292 \quad L_e = 0.0015 \cdot A_{f500r} - 161.56 \quad (3)$$

293

$$294 \quad A_e = 10^{-5} \cdot A_{f500r} + 175.14 \quad (4)$$

295

296 Equation 5 is the root mean square error (RMSE) that represents the accuracy estimator and,
297 the precision estimator given by the standard deviation (SD) (Equation 6), were also determined
298 for Equations 2, 3, and 4. The results related to RMSE and SD are present in Table 3.

299

$$RMSE = \sqrt{\sum_{n=1}^n \frac{(Reference_n - Calculated_n)^2}{n}} \quad (5)$$

301

$$SD = \sqrt{\sum_{n=1}^n \frac{[(Reference_n - Calculated_n) - \overline{(Reference_n - Calculated_n)}]^2}{n-1}} \quad (6)$$

303

304

Table 3

305

306 In summary, this CVS methodology established for the Araguaia river can be explored to
307 estimate the river flow, water level, and altimetry for other rivers around the world.

308

5 Discussion

310

311 Hydrographic data obtained from satellites and other remote sources provide the possibility
312 of broad global coverage for river discharge estimates (Bahadur and Samuels, 2013; Lakshmi,
313 2004). The advances in computing power and data storage capacity associated with the
314 innovations in the satellite remote sensing area are enabling global monitoring of different
315 variables related to the water cycle (Lettenmaier et al., 2015; Wagner et al., 2018). Nowadays,
316 the increase in the number of Planet CubeSats brings images with more cost-effective and higher
317 spatiotemporal resolutions than other commercial satellites (Houborg and McCabe, 2018b).

318 Currently, Planet CubeSat is the only commercial constellation available for capturing daily
319 optical images with high resolution of the entire surface of the Earth. In Brazil, there is a national
320 program (<https://www.gov.br/mj/pt-br/aceso-a-informacao/acoes-e-programas/programa-brasil-mais/>) that provides Planet images with high-resolution (3 m orthorectified per pixel) freely
321 available to governmental institutions throughout the Brazilian territory.

323 Access to the CubeSat images is an important political and economic decision. The use of
324 satellite information is an economical way of measuring river discharge using in situ gauges
325 stations that are costly to install, maintain, and operate (Zaji et al., 2018). According to U.S.

326 Geological Survey (USGS), the cost for a typical in situ gauge station evolves several costs
327 associated with its activities, which are estimated at 41% for labour staff (field and office), 25%
328 for administrative activities, 10% for building and utilities, 10% for field equipment, 7% for data
329 management and delivery, 5% for vehicles and 2% for travel (Norris, 2010). These percentages
330 can vary according to location and conditions, especially in remote areas where in situ gauges
331 stations require expensive field works (Norris, 2010). Besides reducing costs, the implementation
332 of technology-based remote sensing for river discharge can avoid exposing surveyors to
333 dangerous and reacher inaccessible rivers (Samboko et al., 2020).

334 Monitoring of rivers requires a reliable system, being the water level and the river discharge
335 the two essential parameters in this analysis (Mao et al., 2020, 2019, 2018; Mostafavi, 2018).
336 Besides that, the monitoring requires integrated modelling tools that cover adequate spatial and
337 temporal scales involving mathematical applications (Mannschatz et al., 2015). In this context,
338 an innovative methodology for river flow estimation was developed using Planet CubeSat images
339 to detect changes in the flood area surface, which can be used as a CubeSat Virtual Station (CVS).

340 Although methods of river discharge from the direct measurement of width, depth, and
341 velocity (based on velocity-area method) provides a higher level of accuracy than orbital remote
342 sensing (Bjerklie et al., 2005), the proposed methodology used an approach that relies on
343 identifying of the water surface from morphologic features that are easier to recognize from space.
344 The geomorphic features and structural dynamics related to river discharge as channel type,
345 channel slope, channel roughness, depth, and velocity were assumed associated with the river
346 hydraulic geometries and can be used to develop more robust calibration methods.

347 The CVS data obtained were compared with the measures of water level and river discharge
348 of a Conventional Station (CS) and altimetry of the JASON Virtual Sation (JVS), located in the
349 Araguaia River (Brazil).

350 Analyzing the CS data collected in this study, it was found a complete correlation ($R^2 = 1$)
351 between the measurements of water level and river discharge, indicating that the in-situ reference
352 station used was well-calibrated. It was also observed a high correlation of the CS water level
353 measurements with the JVS altimetry data ($R^2 = 0.85$) confirming that the satellite remote sensing

354 can be a useful tool for river flow estimation. Bogning et al., (2018) also found a good correlation
355 ($R^2 > 0.82$) when in-situ gauge records were compared to altimetry- based water levels from
356 multiple satellites, composed of a network of altimetric virtual station (ENVISAT, SARAL,
357 ERS- 2, Sentinel- 3A, JASON- 2, and JASON- 3 data). This analysis was performed in the
358 Ogooué river basin, located at Gabon, with an annual river discharge of 4,750 m³/s and a
359 hydrologic wet-dry regime similar to the characteristics of this study in the Araguaia River. Smith
360 and Pavelsky, (2008) demonstrated that remotely sensed width variations were well correlated to
361 ground measurements of river discharge ($R^2 = 0.81$) when taken days later and hundreds of
362 kilometres downstream. Gleason and Smith (2014) showed that useful estimates of absolute river
363 discharge may be obtained solely from river width using multiple satellite Landsat images,
364 through a characteristic scaling law named At-Many-station Hydraulic Geometry (AMHG), with
365 no ground-based or a priori information. The AMHG was calculated with the monitoring of large
366 extensions (10 to 13 km) from remote sensing along the river.

367 JVS and Landsat can be employed in the case of lacking river rating curves and cross-
368 sectional geometries, as well as when the water levels or flow rates measurements are missing in
369 situ station historic data. However, the use of JVS and Landsat data in a river hydrodynamics
370 context is limited by data coverage in both time and space, which may be insufficient to capture
371 key spatiotemporal variations in water surface elevation daily (Houborg and McCabe, 2018a).
372 Besides that, JVS can be used only to monitor the level of wider rivers (Huang et al., 2018) that
373 intersect with JASON-2 satellite tracks.

374 In this study, the innovative method using Planet CubeSat images provides a possibility to
375 monitor river narrower than those evaluated by JVS and Landsat due to its higher spatial
376 resolution (Houborg and McCabe, 2018b, 2018a). Also, Planet constellation allows monitoring
377 rivers around the world (Kääb et al., 2019) with more flexibility to establish Virtual Stations
378 concerning JVS that are limited to the track satellite intersections. The fact of use high-resolution
379 Planet CubeSat images, with low acquisition inclination, reduces the effect of shadow and
380 increases the river border identification details. This agrees with Bjerklie et al. (2003), who
381 reinforces that even if the river could always be distinguished from the surrounding landscape,

382 narrower channels would have greater uncertainty in the width estimates due to the relative width
383 concerning the resolution of the sources. The altimetry accuracy for the JVS stations varies with
384 the river width, with better precision the wider the channels (Bjerklie et al., 2018), while for the
385 proposed CVS stations the accuracy in determining the level varies with the flooded area close to
386 the station, with precision dependent on the slope at the edges of the channel, as it reflects in the
387 expansion of the flooded area.

388 For the period of study, 8 images were selected with dates correspondent to CS and JVS
389 reference measures. However, many other Planet CubeSat images were available in the period,
390 with 110 cloud-free SR images against 22 JVS measures, representing at least 5 times more
391 information than JVS data for the Araguaia river. Although many Planet images were available,
392 it was decided to use only the images that allowed the comparison with CS and JVS on the same
393 date.

394 The data from CubeSat images showed a well-correlated estimation with river discharge
395 ($R^2 = 96.49\%$) when small lengths of the river (500 m buffer) were analyzed. This correlation was
396 higher than the JVS data and river discharge correlation ($R^2=85.01\%$) that is one of reference
397 adopted by the ANA in Brazil. The results using CubeSat images were also well correlated with
398 CS water level ($R^2 = 94.38\%$) and JVS altimetry ($R^2 = 88.83\%$) when evaluated the flooding area
399 (m^2). According to Papa et al. (2010), ideally, the goal for discharge data accuracy is within $\pm 5\%$
400 related to the true value, but the community agrees that 15% to 20% accuracy is in general
401 acceptable for discharge measurements.

402 Virtual stations with CubeSat images showed greater accuracy and precision at lower river
403 discharge rates whereas JASON virtual stations have greater accuracy and precision for higher
404 river discharge rates. This is observed by the fact that in the CVS, a better refinement of the
405 flooded area is possible even with the presence of sandbanks while the JVS presents greater noise
406 in the identification of the altimetry related to these areas. At higher river discharges, we observed
407 that the JVS presented better details of the altimetry, especially when the increase in the level of
408 the river occurred inside the channel without accompanying the expansion of the flooded area.

409 In this study, it was visually observed a refined design of the flooded areas due to the
410 resolution of the CubeSat images. From this observation, an attempt was made to find a
411 relationship between the width of the river and a buffer size that provided less demand of image
412 areas to achieve a high Pearson coefficient. It was observed that a buffer ranging from 0.5 to 1
413 times the average width of the studied river section allowed to reach these results, remaining
414 stable even the value of R^2 . Then, the proposed methodology allows the use of less than 388 km²
415 of images/year for this virtual station, representing an advantage in comparison with the AMGH
416 methodology, which suggests the evaluation of multiple river widths by stretches greater than 10
417 km. Using 3-meter Planet images as reference, Pôssa et al. (2018) observed a slightly increased
418 precision in the water surface delineation compared to Landsat and Sentinel images due to spatial
419 resolution of satellite images.

420 Overall, these experiments allow us to employ a simple exponential equation model with
421 daily CubeSat images for well predict the river flow at a monthly scale, based on the surface
422 hydrological information measured from space as proof of concept and utility of the method. The
423 use of new constellations, new hydrological science methods, and advancements in resolutions
424 (spatial, temporal, and radiometric) of remote sensing make possible the application of monitoring
425 increasingly smaller watersheds, as they have coverage of several pixels and more frequent data
426 acquisitions (Lakshmi, 2004). Besides that, to flow estimation measurement, the CubeSat images
427 can be used to study other processes related to data assimilation; flood monitoring and prediction;
428 floodplain connectivity (Cooley et al., 2017); land surface characteristics (land use, temperature,
429 snow cover) (Reichle, 2008); image fusion to land use mapping and monitoring (Houborg and
430 McCabe, 2018b; Joshi et al., 2016); and water quality monitoring (Maciel et al., 2020).

431

432 **6 Conclusion**

433

434 An innovative method for semi-automated river flow estimation using Planet CubeSat data
435 was developed to detect changes in the surface of the flood area, using the Araguaia River as a
436 testbed. In summary, the flood areas detected by CubeSat data showed significant correlations
437 with river discharge and water level measurements from gauge-based Conventional Station (CS)
438 in small areas of the river using a reduced amount of satellite images. CubeSat data also presented
439 a significant correlation with altimetry measurements from JASON-2 Virtual Station (JVS)
440 officially adopted by the Brazilian agency, with the advantage to provides greater records
441 numbers per year, more flexibility of position for Virtual Stations establishment, and the
442 possibility to monitor narrower rivers. The river discharge extracted from Cubesat data showed a
443 higher correlation with CS than JVS, indicating that CVS had more capacity of reproducing the
444 ground truth compared to JVS.

445 In the future, this method can be completely automated to fill the gaps in the streamflow
446 series, to compute different riverine contributions in the sub-basin, and to promote an
447 understanding of river discharge spatial distribution on a near-real-time for entire continents. This
448 method can also be used as a cost-effective alternative to monitoring the sub-basin discharges,
449 improving water management, particularly, in developing countries where the presence of
450 conventional stations is limited.

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452

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456 (<https://www.planet.com/explorer>).

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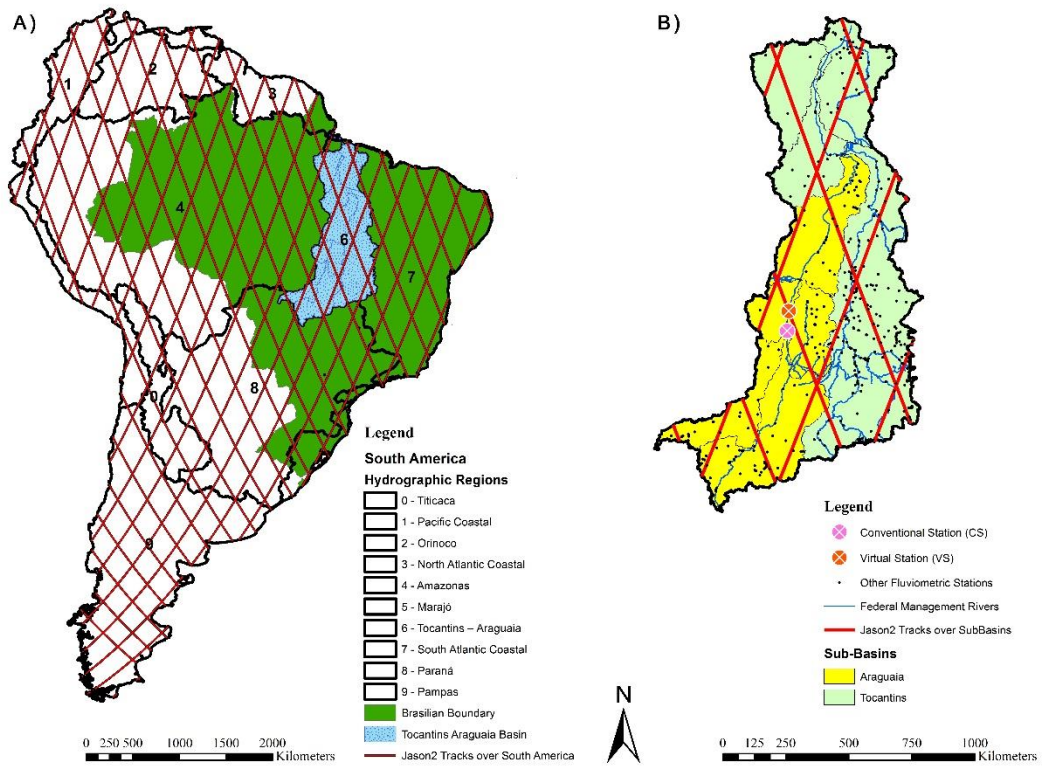
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601 Simulating and Forecasting River Discharge. *IEEE Trans. Geosci. Remote Sens.* 56, 3432–3441.
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603

604 **Figures**

605

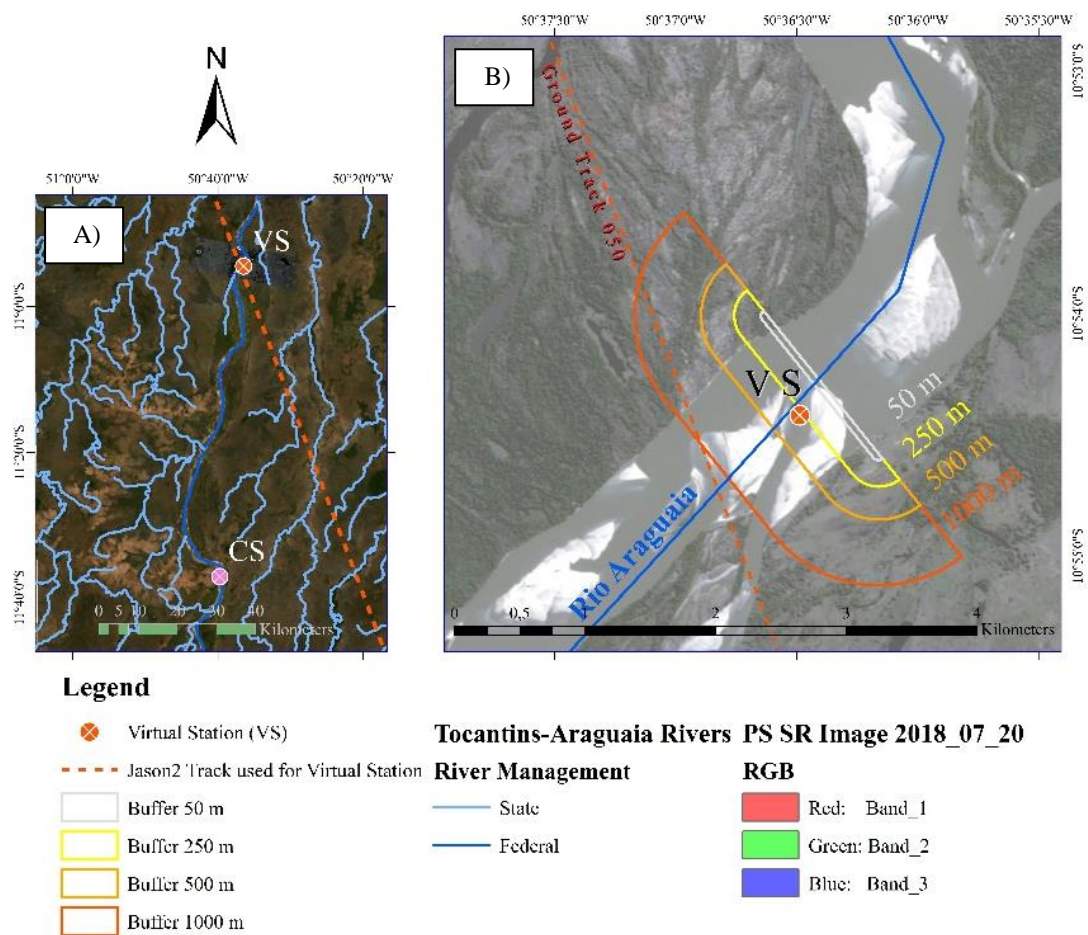
606 **Fig. 1.** Overview of the study area. (A) Overview of South America with its 10 Hydrographic Regions
607 (black), passes of JASON-2 over the area (red) and, the Tocantins-Araguaia basin (light blue); (B) Zoom
608 in the Tocantins (light-green) - Araguaia (yellow) basin boundaries, presence of rivers with federal
609 regulation (blue) and all fluviometric in situ stations (black dots), complemented by tracks of Jason-2 (red)
610 highlighting JVS (red circle; north) and CS (pink circle; south) ground references.



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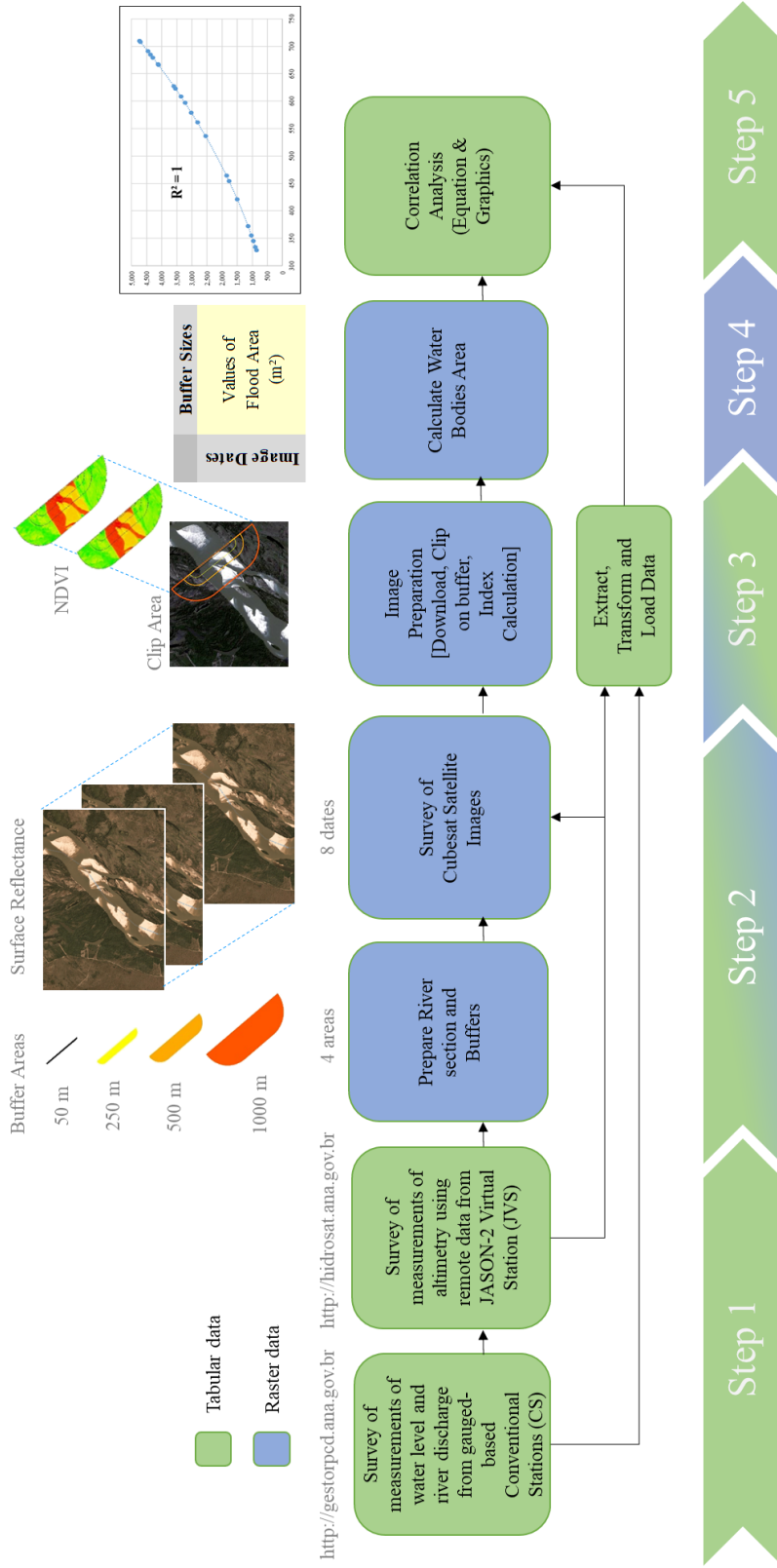
613 **Fig. 2.** The study area of the Araguaia sub-basin. (A) Zoom in the Araguaia River (center) highlighting the
 614 track of Jason-2 (red) over the surface drainage (blue), and the Conventional Station (CS) used as ground
 615 truth (pink dot). The region where the Jason-2 track crosses the Araguaia River is the Virtual Station (JVS)
 616 far 78 km from CS and, the region used to download the CubeSat SR images;
 617 over the Araguaia River (blue line) with the 4 different buffer areas used in the methodology (50 m – grey;
 618 250 m – yellow; 500 m – orange; 1000 m – red). In the background it is presented the Surface Reflectance
 619 (SR) Planet image from July, 20th 2018 with 50% transparency and the representation of the Jason-2 track
 620 over the region (red dashed line).
 621



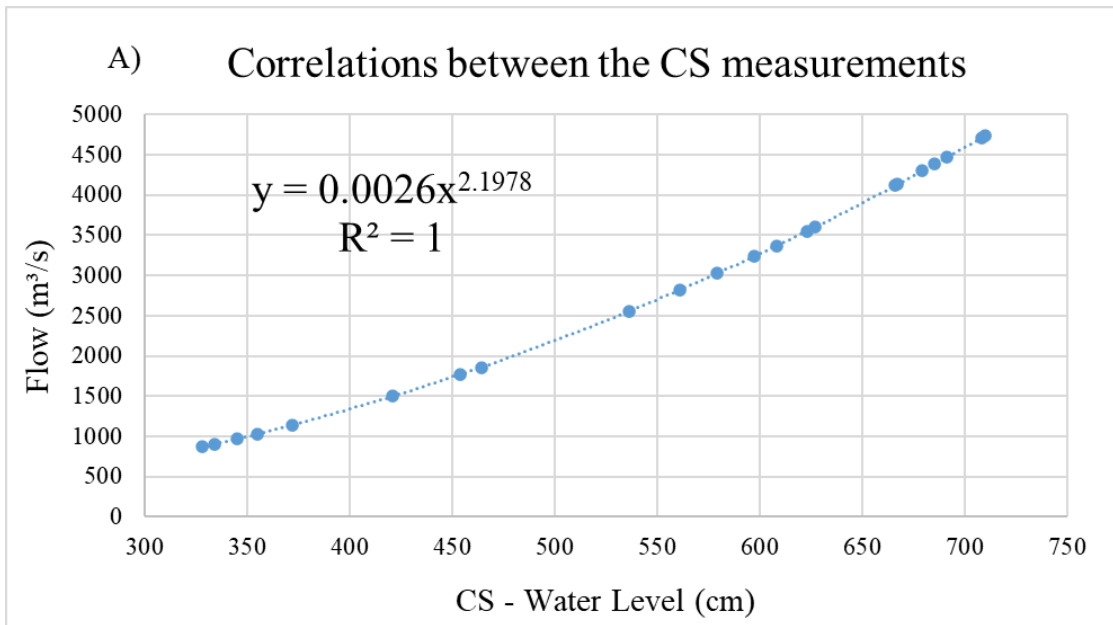
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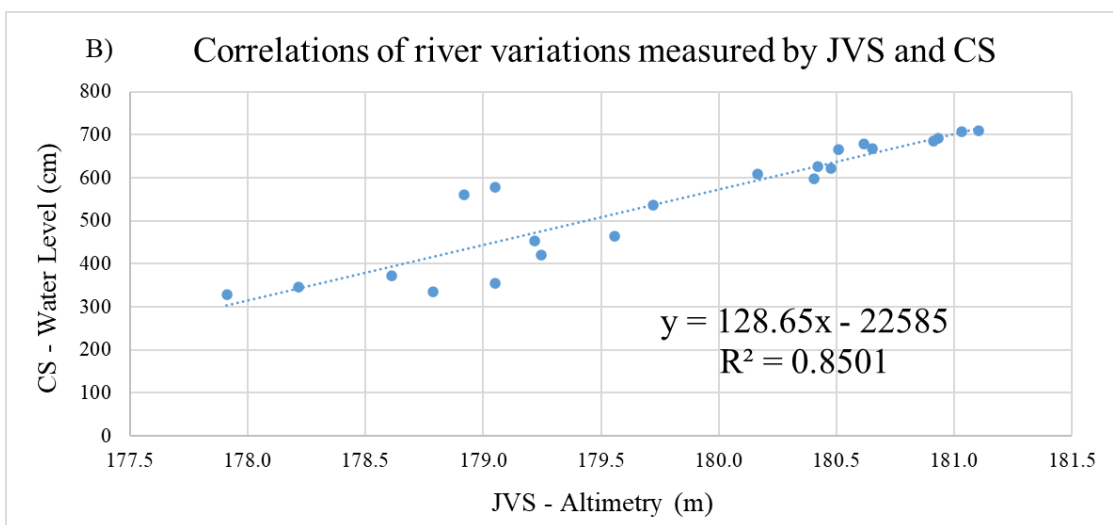
624 **Fig. 3.** Methodological framework using CubeSat to estimate the river flow. The 1st step is used for
625 gathering reference information to support the key-curves. In the 2nd step are prepared the specific buffer
626 areas and selected the CubeSat images to investigate the correlation between inundation extent and river
627 flow. The 3rd step is used for preprocessing selected CubeSat images with pixel classification (water/no-
628 water) based on NDVI values. In the 4th step are calculated the flooding area for each image. The last step
629 is to evaluate the regression analysis comparing the 3 reference data (CS - Flow river; CS – Water Level;
630 JVS – Altimetry).



632 **Fig. 4.** Evaluation of the reference data. **(a)** Relationship between the river level (x-axis) and flow (y-axis)
 633 by the CS in the São Felix do Araguaia/MT station for the period of analyses. The blue curve represents
 634 the exponential equation ($y = 0.0026x^{2.1978}$) that are well adjusted with $R^2 = 1$.
 635 **(b)** Relationship between the altitudes (x-axis) calculated by the JVS and the quotes determined on the
 636 water level (y-axis) by the CS in the Araguaia basin for the period of analyses. The blue curve represents
 637 the linear equation ($y = 128.65x - 22585$) with $R^2 = 0.8501$. In both figures, the solid blue circles represent
 638 correlated values with 10 days interval.
 639



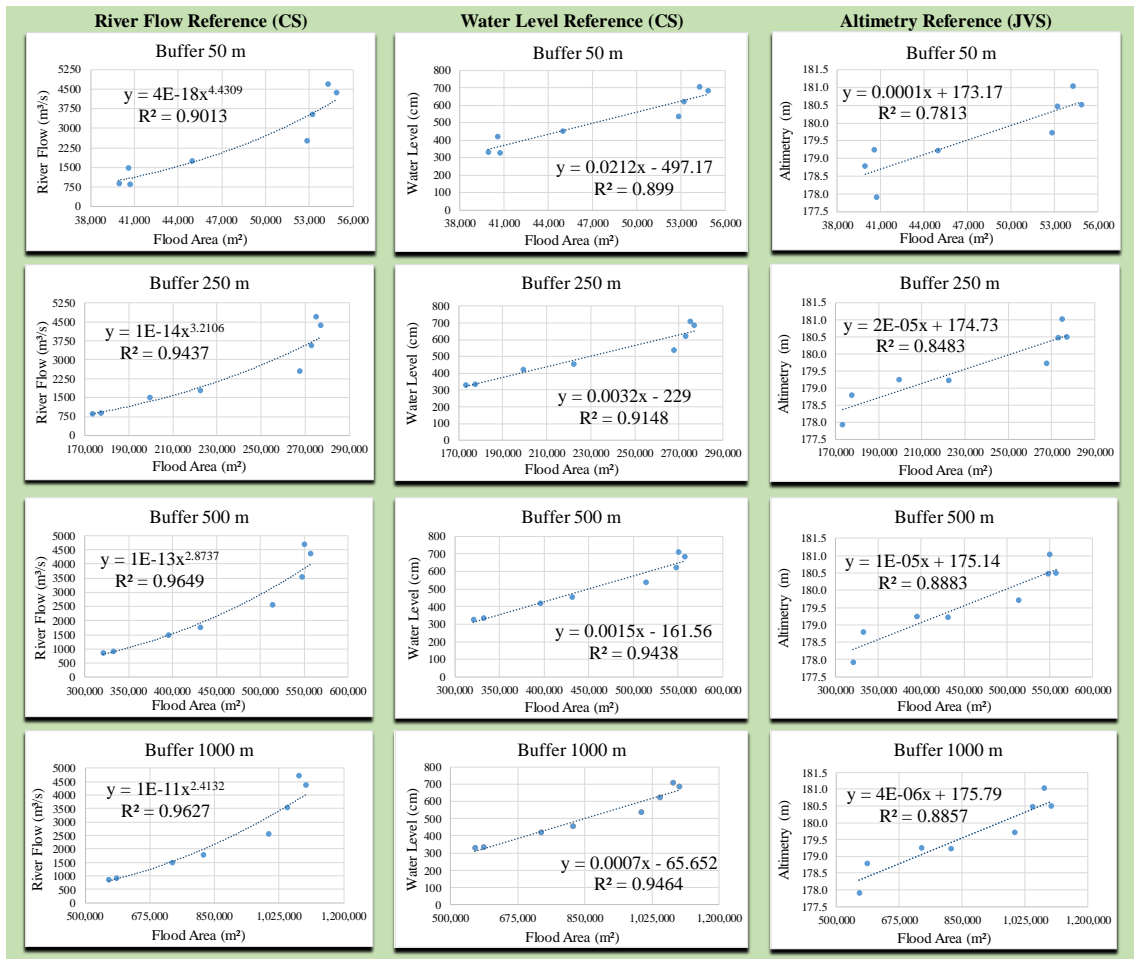
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643 **Fig. 5.** Regression curves against 3 ground references and 4 different buffer sizes

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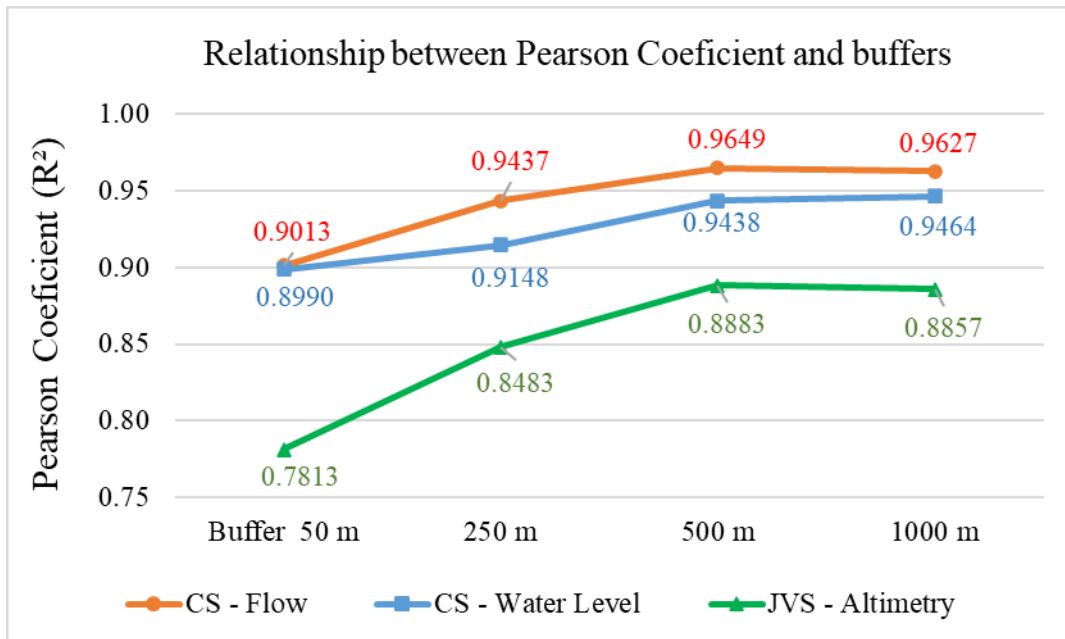


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646

647 **Fig. 6.** Relationship between R^2 (x-axis) and 4 buffers distances (y-axis) for 3 sets of reference data (CS
648 water level and river flow and JVS altimetry).

649



650

651

652 **Tables**

653

654 **Table 1.** Detail of measurements related to JVS, CS, and satellite images used in the period of analysis
 655 for river flow estimates.

656

Label ID	Date	JASON	Conventional	Conventional	Surface Reflectance
		Virtual Station (JVS) Altimetry (m)	Station (CS) Water Level (cm)	Station (CS) River Flow (m ³ /s)	(SR) Planet CubeSat Images
1	2018 01 03	179.049	579	3,022.10	incomplete/cloud
2	2018 01 13	178.917	561	2,819.00	incomplete/cloud
3	2018 01 23	180.478	623	3,551.62	available
4	2018 02 02	180.404	597	3,233.03	incomplete/cloud
5	2018 02 12	180.165	608	3,365.81	incomplete/cloud
6	2018 02 22	180.615	679	4,294.38	incomplete/cloud
7	2018 03 04	181.030	708	4,709.77	available
8	2018 03 13	181.103	710	4,739.20	incomplete/cloud
9	2018 03 23	180.913	685	4,378.59	incomplete/cloud
10	2018 04 02	180.931	691	4,463.70	incomplete/cloud
11	2018 04 12	180.651	667	4,128.66	incomplete/cloud
12	2018 04 22	180.508	666	4,115.01	available
13	2018 05 02	180.419	627	3,602.11	incomplete/cloud
14	2018 05 12	179.721	536	2,549.77	available
15	2018 05 22	179.557	464	1,856.67	TOA image
16	2018 06 01	179.220	454*	1,769.96*	available
17	2018 06 11	179.248	421	1,499.74	available
18	2018 06 21	178.612	372	1,143.57	TOA image

19	2018 07 01	179.049	355	1,032.33	incomplete/cloud
20	2018 07 10	178.217	345	969.81	incomplete/cloud
21	2018 07 20	178.786	334	903.52	available
22	2018 07 30	177.912	328	868.46	available

* average between 02/06/2018 and 31/05/2018

657

Label ID	Date	JASON Virtual Station (JVS) Altimetry (m)	Conventional Station (CS) Water Level (cm)	Conventional Station (CS) River Flow (m³/s)	Surface Reflectance (SR) Planet CubeSat Images
1	2018 01 03	179.049	579	3,022.10	incomplete/cloud
2	2018 01 13	178.917	561	2,819.00	incomplete/cloud
3	2018 01 23	180.478	623	3,551.62	available
4	2018 02 02	180.404	597	3,233.03	incomplete/cloud
5	2018 02 12	180.165	608	3,365.81	incomplete/cloud
6	2018 02 22	180.615	679	4,294.38	incomplete/cloud
7	2018 03 04	181.030	708	4,709.77	available
8	2018 03 13	181.103	710	4,739.20	incomplete/cloud
9	2018 03 23	180.913	685	4,378.59	incomplete/cloud
10	2018 04 02	180.931	691	4,463.70	incomplete/cloud
11	2018 04 12	180.651	667	4,128.66	incomplete/cloud
12	2018 04 22	180.508	666	4,115.01	available
13	2018 05 02	180.419	627	3,602.11	incomplete/cloud
14	2018 05 12	179.721	536	2,549.77	available
15	2018 05 22	179.557	464	1,856.67	TOA image
16	2018 06 01	179.220	454*	1,769.96*	available
17	2018 06 11	179.248	421	1,499.74	available
18	2018 06 21	178.612	372	1,143.57	TOA image
19	2018 07 01	179.049	355	1,032.33	incomplete/cloud
20	2018 07 10	178.217	345	969.81	incomplete/cloud
21	2018 07 20	178.786	334	903.52	available
22	2018 07 30	177.912	328	868.46	available

* average between 02/06/2018 and 31/05/2018

658

659 **Table 2.** Flood area calculated inside buffers with NDVI value smaller than 0.15.

660

Label ID	Selected dates of Surface Reflectance (SR) Planet CubeSat Images	Flood Area	Flood Area	Flood Area	Flood Area
		inside	inside	inside	inside
		Buffer	Buffer	Buffer	Buffer
		50m (m²)	250m (m²)	500m (m²)	1000m (m²)
3	2018 01 23	53.181	273.024	547.929	1,046,745
7	2018 03 04	54.261	275.040	550.251	1,079.640
12	2018 04 22	54.846	276.984	557.586	1,097,469
14	2018 05 12	52.839	267.615	513.891	997.580
16	2018 06 01	44.964	222.336	431.730	819.477
17	2018 06 11	40.572	199.512	395.604	736.335
21	2018 07 20	39.924	177.471	332.415	585.909
22	2018 07 30	40.707	173.313	320.805	563.895

661

662 **Table 3.** Accuracy (*RMSE*) and precision (*SD*) estimators related to river flow (*Qe*), water level (*Le*) and
663 altimetry (*Ae*)
664

Regression Curves	Accuracy Estimator (<i>RMSE</i>)	Precision Estimator (<i>SD</i>)	Unit
River Flow (<i>Qe</i>)	717,59	553,63	m ³ /s
Water Level (<i>Le</i>)	59,45	37,16	cm
Altimetry (<i>Ae</i>)	0,33	0,34	m

665