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A Multi-Method Approach to Flood Mapping: Reconstructing Inundation Changes in the Cambodian Upper Mekong Delta

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Abstract

As in many tropical deltas globally, annual floods shape the livelihoods of the largely rural population in the Cambodian Mekong delta. Agricultural cycles are keyed to the flood arrival, peak, and recession, and fish populations depend on inundated floodplains for their regeneration. However, as factors like climate change and hydropower infrastructure development are altering the Mekong's hydrology, the inundation dynamics of its deltaic floodplains are shifting as well. Several studies have assessed the general changes of river discharge and flood extent on a basin- or delta-wide scale. Yet the sustainable development of this region is relying on dynamics at more local and specific scales, which have not been addressed so far.

This paper presents a methodology to track the evolution of hydrological regimes and associated inundations in tropical deltas such as the upper Mekong delta in Cambodia, where it is applied over the past 30 years. Data scarcity and heterogeneity of the environment in this region necessitated the use of combined approaches. We established a link between water levels measured in-situ and

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flood maps derived from optical and radar satellite images (Sentinel-1 and -2). The robustness of the link was assessed using Sentinel, Landsat imagery and the TanDEM-X (12m) elevation model. This water level-flood link (WAFL) was then used to reconstruct a daily time series of inundation extents reaching back to the beginning of hydrological measurements in 1991 (30 years). On this basis, changes in the incidence, duration, and spatial distribution of floods were analysed.

The results indicated that WAFL can be used to reconstruct inundation maps with an overall robustness of 87% in comparison to historical inundation maps derived from remote sensing imagery. Comparisons of WAFL-derived flood extents with Landsat images further underscored the significant role of local infrastructure, sedimentation dynamics, and land cover to explain changes in inundation dynamics. WAFL-based analyses revealed that inundation durations have decreased by an average of 19 days when comparing the periods before and after 2008, which was identified as a break point in the hydrological time series. Furthermore, a drastic decrease in inundation the annual frequency with which individual pixels are flooded can be detected during the first half of the traditional flood season, with an average of -21% in early August, negatively impacting water-based livelihoods, from agriculture to fisheries.

Keywords: Mekong delta, Cambodia, inundations, Sentinel-1 and -2, water levels

1. Introduction

Tropical deltas worldwide are fundamentally influenced by regional and local hydrological regimes (Kuenzer and Renaud, 2012; Loucks, 2019). Given low terrain gradients, inundation processes are central to their populations' water-based livelihoods. Yet it is often not well-understood what impact large-scale, basin-wide changes have on more local systems, often due to a lack of data. This is illustrated perfectly by the Cambodian Mekong Delta.

As the largest trans-boundary river in Southeast Asia, the Mekong plays a crucial role in the socioeconomic development of the region, with agriculture and fisheries highly dependent on its flow regime (Kondolf et al., 2018; Boretti, 2020; Kummu and Sarkula, 2008). However, recent years have seen considerable shifts in the Mekong's hydrology (Yun et al., 2020; Trung et al., 2020). Its seasonal hydrological regime, defined by a flood pulse - a strong unimodal flow pattern induced by the annual Monsoon precipitation - has altered in terms of timing and magnitude. On a basin-wide scale, numerous studies have traced the reasons for this to a variety of factors, especially hydropower development and climate change (Hecht et al., 2018; Lacombe et al., 2014; Yang et al., 2019; Yun et al., 2020; Li et al., 2017; Pokhrel et al., 2018). For example, Hoang et al. (2019) project that dry season flows in the basin will more than double as a result of hydropower development, while wet season flows will decrease by 16% by 2050. Similarly, Hoang et al. (2016) conclude that climate change will result in a decrease of wet season flows by 7%, and an increase in dry season flows by 33% by 2065.

These basin-wide changes have a particularly adverse impact on downstream hydro-ecological systems in the Cambodian and Vietnamese Mekong Delta (Intralawan et al., 2018; Yoshida et al., 2020). In these areas, the annual inundations¹ fundamentally shape the livelihoods of the local population. They deposit nutrient-rich sediments on the floodplains, benefiting flood-recession agriculture,

¹This paper uses the terms "flood" and "inundations" synonymously.

29 contribute to the recharge of soil moisture and groundwater after the dry season
30 months (Dang et al., 2018; Kondolf et al., 2018) and are crucial for the repro-
31 ductive cycles of fish species, supporting one of the world’s most productive
32 systems of inland fisheries (Poulsen et al., 2004; Hurtle, 2009; Winemiller et al.,
33 2016). The floodplains of the Mekong are significantly impacted by shifts in the
34 incidence, duration, and spatial patterns of annual inundations as a consequence
35 of basin-wide hydrological changes. This mirrors the situation in other major
36 deltas worldwide, such as the Ganges–Brahmaputra and Amazon deltas (Szabo
37 et al., 2016; Singha et al., 2020).

38 These factors have mostly been studied at large scales, based on different hy-
39 drological and hydrodynamic models or on past series of remote sensing imagery
40 (Heng et al., 2021; Try et al., 2020; Li et al., 2019; Shin et al., 2020; Mohammed
41 et al., 2018; Burbano et al., 2020). However, each of the proposed modeling ap-
42 proaches comes with its own limitations and simplifying assumptions, as well as
43 with a challenge regarding parametrisation in these often relatively data-sparse
44 regions of interest. In terms of remote sensing, freely accessible, consistent long-
45 term image time series such as Landsat and MODIS can provide some insights
46 into how the spatial patterns of inundations have shifted (Aires et al., 2020;
47 Dang et al., 2016; Fayne et al., 2017). However, many of these series are limited
48 in terms of the temporal and spatial resolution of images, and, in the case of
49 optical images, exhibit data sparsity during the wet season due to cloud cover.
50 They also have difficulties accounting for water areas dissimulated by natural
51 vegetation. Due to the limitations inherent in each approach, the existing studies
52 are unable to produce both sufficiently extensive time series and adapted spatial
53 and temporal resolutions for analysing long-term flood dynamics at local scales.
54 An alternative path is now available in the form of the Sentinel constellation
55 by the European Space Agency (ESA). Its Sentinel-1 and 2 satellites, launched
56 between 2014 and 2017 (Potin et al., 2019), provide freely available optical and
57 SAR data, at a return period of five to six days and a spatial resolution of up
58 to 10 m. This makes Sentinel a valuable basis to better understand dynamic
59 hydrological processes, such as inundations, at local scales. Both Sentinel-1 and

60 -2 data have been widely used in hydrological applications, separately and in
61 combination (Twele et al., 2016; DeVries et al., 2020; Tsyganskaya et al., 2018),
62 including on delta floodplains (Quang et al., 2019; Singha et al., 2020; Pham-
63 Duc et al., 2017). However, the disadvantage of the Sentinel series lies in its
64 comparatively short duration, which makes it impossible to observe long-term
65 trends.

66 The aim of the present paper is to present a new methodology to analyse
67 long-term flood dynamics in data-sparse tropical deltas, in order to infer the
68 impact of basin-wide hydrological alterations on local hydro-ecological systems.
69 To circumvent barriers of data scarcity and limitations of any single method,
70 we are proposing a novel multi-method approach to reconstruct a time series of
71 daily inundation extents. The application of this approach is illustrated in the
72 Cambodian upper Mekong delta, based on local water level measurements since
73 1991 and on Sentinel-derived flood maps.

74 Building on an in-depth qualitative understanding of international develop-
75 ment relations and agricultural practices grounded in social sciences and ac-
76 quired through interviews with farmers and key informants over the last five
77 years (Venot and Jensen, 2021), the proposed solution is to link in-situ water
78 levels with high-resolution inundation maps derived from Sentinel imagery to
79 establish a water level - flood link (WAFL). On the basis of this link, daily
80 inundation maps are reconstructed going back to 1991, and then used to as-
81 sess changes in inundation incidences, durations, and spatial patterns. This
82 approach helps overcome the paucity and heterogeneity of data available in the
83 area. We further assess the robustness of the WAFL using comparisons with
84 inundation extents and land cover parameters derived from Landsat imagery
85 and the TanDEM-X (12 m) digital elevation model (Rizzoli et al., 2017; Hawker
86 et al., 2019).

87 **2. Study Area**

88 Agriculture, fisheries and livelihoods of the Cambodian upper Mekong delta
89 are deeply influenced by annual monsoon inundations, yet few studies so far
90 have focused on understanding the hydrological dynamics of this area. With a
91 few notable exceptions (Sothea et al., 2006; Heng et al., 2021; Orieschnig et al.,
92 2021), studies have instead focused on the Vietnamese Mekong delta. However,
93 the Cambodian side of the delta exhibits several striking differences to its Viet-
94 namese counterpart - most importantly in terms of water control infrastructure.
95 On the Vietnamese side of the border, an extensive dyke and sluice gate system
96 allows considerable anthropogenic control over inundations (Park et al., 2020;
97 Triet et al., 2017; Quoc Thanh et al., 2019). Such infrastructure is largely ab-
98 sent in the Cambodian part of the delta. Consequently, it can be conjectured
99 that the effects of upstream alterations are more immediately evident in the
100 inundation patterns of this region (Aires et al., 2020).

101 The study area is located 60 km south of the Cambodian capital Phnom
102 Penh, on the banks of the Mekong and its distributary, the Bassac river. The
103 Koh Khel and Neak Luong hydrological stations are located just north of the
104 study area, on the Bassac and Mekong respectively. Furthermore, the Chau
105 Doc and Tan Chau stations can be found a few kilometres south of the case
106 study area, in Vietnam (see Figure 1).

121 essential component of the daily diet of the local population, and represent a
122 significant share of the revenues of the poorest households in the region (Vilain
123 et al., 2016). During the flood, fish populations regenerate on the floodplains
124 (Hortle, 2009). Fish spawn either directly in the remaining expanses of uninun-
125 dated natural vegetation, or migrate from upstream in their juvenile stages to
126 safely mature in the nutrient-rich shallow waters on the deltaic plains. When
127 flood recession sets in, species migrate back to the main stream of the river, its
128 distributaries, or smaller bodies of inland water, where they are later caught by
129 local fishermen (Vu et al., 2021; Poulsen et al., 2004).

130 The study area is further divided into two sub-zones with different agricul-
131 tural landscapes. The first region of interest (Zone A) is located on the right
132 bank of the Bassac (see Figure 1). It encompasses a total area of 206.75 km². Its
133 western and northern border are defined by a small distributary of the Bassac,
134 its southern one by the Vietnamese border. Its landscape is characterised by
135 Prek channels. These are human-made, trapezoidal channels, 10 to 50 meters
136 wide and a few kilometers long, which diverge perpendicularly from the Bassac's
137 main stream and connect it to low-lying floodplains by breaching the elevated
138 river banks. In terms of agriculture, a gradient of cultivation can be observed
139 along the length of each Prek. In areas that have been sufficiently raised by
140 sediment deposition and are now rarely flooded (called *Chamkar*), high-value
141 crops such as fruit trees and various vegetables are grown (Pinn et al., 2020). The
142 further the terrain slopes away towards low-lying, regularly flooded areas (*Boe-*
143 *ungs*), the more these crops give way to rice and maize.

144 The second area of interest (Zone B) is located on the opposite bank of the
145 Bassac, and is bracketed between the Bassac in the West and the Mekong in
146 the East (see Figure 1). In the North, it is limited by a canal and a dyke, in
147 the South by the border to Vietnam. It covers an area of 312.65 km². This
148 zone is characterized by a large interior floodplain, part of which feature man-
149 made depressions, remnants of shallow reservoirs that were excavated during
150 the Khmer Rouge period in the 1970s. Connecting these depressions to natural
151 streams, a network of canals - also dug during the Khmer Rouge period and

152 re-excavated since then - spans across the area. Together, these structures
153 support extensive areas of rice cultivation, with cropping calendars attuned
154 to topography and flood timing. Recession rice, planted just after the flood,
155 benefits from residual soil moisture and precipitation in December and January,
156 which reduces the need for irrigation. A second rice crop, dry season rice, is
157 sometimes planted between February and April, though the extent of this crop
158 is usually limited by a lack of irrigation water, which needs to be pumped from
159 canals and shallow reservoirs. Subsequently, early wet season rice is planted
160 in late April or May. It is partially irrigated if water is available, but depends
161 largely on the increased rainfall amounts in late April, May, and June. Typically,
162 it is harvested just before the start of the flood in July.

163 When the timing, spatial patterns, and magnitude of inundations vary, spe-
164 cific problems result for agriculture, fisheries, and ecosystems in general (Nguyen
165 et al., 2019). For instance, if floods arrive too soon, early wet season crops can
166 be damaged or lost. In contrast, if inundations are shorter than expected, soil
167 moisture and groundwater recharge can be insufficient, and reproduction times
168 for fish populations are cut short. Similarly, a late flood recession can be prob-
169 lematic since it results in recession crops being planted with a delay, meaning
170 flowering and harvesting may be negatively affected by dryer weather. Conse-
171 quently, the need for irrigation is increased, which can cause issues given the
172 lower water availability and higher overall production costs resulting from pump
173 operation (Koponen et al., 2017). For these reasons, it is crucial to understand
174 the spatial and temporal patterns of inundations in the area and their changes
175 over the past decades.

176 3. Methodology

177 An overview of the methodology employed in this analysis is given in Figure
178 2.

179 The multi-method approach proposed in this paper is grounded in over five
180 years of interdisciplinary research conducted by the authors. Through months

181 of collective field work, frequent interviews with multiple stakeholders, and in-
182 situ water level measurements, the team acquired qualitative understanding
183 regarding the development projects implemented in the area, local agricultural
184 practices, and local hydrological processes. This understanding provided the
185 context for the proposed approach, coupling remote sensing methods and hy-
186 drological analysis to study inundation trends in the Cambodian Upper Mekong
187 delta.

188 First, an analysis of local hydrological trends and break points is carried out,
189 to see if changes observed in the upper Mekong delta line up with basin-wide
190 trends. Second, a water level - flood link (WAFL) is established. This is achieved
191 by deriving a time series of inundation extents from Sentinel-1 and -2 imagery,
192 and then linking them to locally measured water levels using a correlation model
193 to take into account propagation delay times. As a third step, a time series of
194 inundation extents is back-calculated on the basis of WAFL.

195 The robustness of the WAFL is assessed using Sentinel and Landsat images,
196 as well as the TanDEM-X digital elevation model (12 m resolution). For one
197 thing, WAFL-derived inundation extents are compared to inundation maps di-
198 rectly derived from Landsat and Sentinel-2. For another, they are compared to
199 inundation extents derived from TanDEM-X. In addition, the effect of local land
200 cover variables, especially natural vegetation such as shrubland and trees, on
201 the inundation classification are evaluated using a land use land cover (LULC)
202 classification based on Landsat images.

203 Finally, the changes in inundation incidences and durations in the Cambo-
204 dian upper Mekong delta over the past three decades are quantitatively and
205 qualitatively assessed according to break points derived from the hydrological
206 analysis.

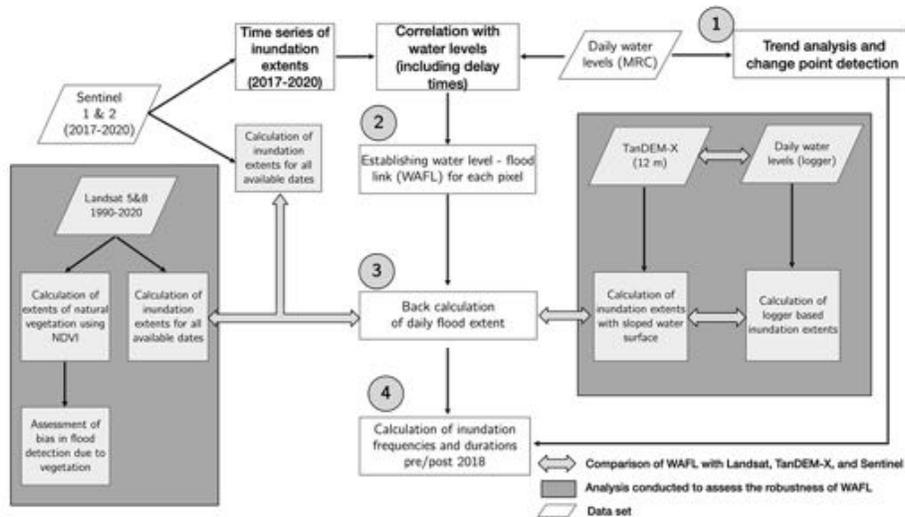


Figure 2: Overall analysis workflow

207 3.1. Hydrological Analysis: Identifying Trends and Change points

208 The hydrological analysis was carried out on the time series of water lev-
 209 els measured at four hydrological stations maintained by the Mekong River
 210 Commission (MRC). First a trend analysis was implemented using the non-
 211 parametric Mann-Kendall test (Hamed and Ramachandra Rao, 1998). Then,
 212 a change point detection was carried out using the Pettitt test (Pettitt, 1979),
 213 Buishand’s range test (Buishand, 1982), and the standard normal homogeneity
 214 test (SNH, Alexandersson (1986)). This approach follows the analyses by Mal-
 215 lakpour and Villarini (2016), Yun et al. (2020), and Zhou et al. (2019). The
 216 parameters tested were the dates of the flood rise and recession, the overall
 217 flood duration, the duration of water levels above local thresholds, the average
 218 water level during the flood, and the maximum water level, along with the date
 219 at which it was reached each year (see Appendix A in supplementary materials
 220 for further explanations). All elevations are given in the local Ha Tien 1960
 221 elevation datum.

222 The hydrological stations used in this analysis are Koh Khel and Chau Doc
 223 on the Bassac, and Neak Luong and Tan Chau on the Mekong (see Figure 1)

224 At Koh Khel, a continuous time series of daily water level measurements since
225 autumn 1991 is available. At Neak Luong, a series is available since 1926, which
226 is remarkably complete save for two larger gaps in 1946 and 1952-3. For this
227 series, the tests were carried out twice: once on the entirety of the series, and
228 once on a shortened series corresponding to the same duration as that available
229 at Koh Khel. At both Chau Doc and Tan Chau series are available since 1980
230 and the analysis was conducted on the entirety of the series.

231 *3.2. Detecting Flood Extents Using Sentinel-1 and 2*

232 A series of flood maps was generated from SAR Sentinel-1 and optical
233 Sentinel-2 images for the period 2017-2020. 2017 was chosen as a starting point
234 because the satellite constellation was fully in place beginning that year. For
235 this purpose, the series of Sentinel-1 and 2 images available on the cloud com-
236 puting platform Google Earth Engine (Gorelick et al., 2017) was analysed. Past
237 studies have illustrated the synergy effects for flood detection in combining
238 both optical and SAR images, for Sentinel in particular (DeVries et al., 2020;
239 Bioresita et al., 2019; Huang et al., 2002). Images were subjected to various pre-
240 treatments. Sentinel-2 images were atmospherically corrected using the sen2cor
241 algorithm (Main-Knorn et al., 2017) and clouds were masked based on the QA
242 band. Sentinel-1 images underwent pre-processing based on the European Space
243 Agency’s Sentinel-1 toolbox. Metadata was updated with a restituted orbit file,
244 border noise and thermal noise were removed, and radiometric calibration and
245 orthorectification were applied. In addition, a refined Lee speckle filter (Lee,
246 1983) was implemented.

247 To classify each image into flooded and not flooded areas, three spectral
248 indices were first calculated for the optical images: the Normalized Difference
249 Vegetation Index (NDVI, Rouse J.W. et al. (1974)), the Normalized Difference
250 Moisture Index (NDMI, Wilson and Sader (2002)) and the Normalized Differ-
251 ence Water Index (NDWI, McFeeters (1996)). For the optical images, these
252 three indices were used as input bands for classification. For Sentinel-1, the VH
253 and VV band were selected. On this basis, an unsupervised K-means classifi-

254 cation approach was chosen (Arthur and Vassilvitskii, 2007; Frank et al., 2016)
255 to identify flooded areas in both Sentinel-1 and -2 images. This classification
256 approach was selected because it can be applied equally to optical and SAR
257 images, and because no local calibration of threshold values is required. As the
258 training period for the classifier, a time window during the 2018 wet season -
259 from September 25 to October 01 - was used due to the large flood extents and
260 sharp contrast between open water and dry areas at this time. Validation of
261 the flood classification was carried out using a total of 2340 points, set manu-
262 ally on the basis of SPOT-6 high-resolution imagery, on four different dates at
263 different stages during the flood cycle: 2017/01/29, 2018/06/24, 2018/08/04,
264 and 2019/01/27. On this basis, a confusion matrix and the kappa coefficient
265 (Congalton, 1991) of the classification were calculated. This data was also used
266 to determine the optimal number of clusters, which was determined to be two.
267 After validation, the classifier was applied to the entire collection of Sentinel
268 images, and the extents of open water areas were extracted for each image. Fi-
269 nally, the time series of inundation extents was exported, smoothed using a 3-day
270 rolling mean, and scaled down to a daily time step using linear interpolation.

271 3.3. Establishing a Water Level - Flood Link (WAFL)

272 In the dynamics of inundations on large floodplains, a temporal lag is typi-
273 cally observed between the change in river water level and the change in flood
274 extent (Zhang et al., 2017). Time is needed to fill the water bodies when the
275 river flood occurs, accounting for a temporal lag between the flood dynamics
276 and the river water levels. Similarly, the flood recession on the floodplains is out
277 of phase with the river water level drop, since inundated areas decrease more
278 slowly due to the retention of water by dykes and other floodplains structures.
279 This results in hysteresis effects on the relationship between river water levels
280 and the inundated surfaces (Hughes, 1980; Kummur et al., 2014). Lag times
281 are controlled by the ease with which water can flow between the river and
282 the floodplains, depending on hydraulic controls such as dykes, canals, bank
283 heights, local topography, and water level gradients. Physically-based models

284 require geometric data of the main hydraulic connections and dykes, which are
285 not accessible at this scale. Even high-resolution DEMs are often insufficient
286 in terms of horizontal resolution and vertical accuracy to capture the hydraulic
287 controls by dykes in the area, many of which are below 1 m in height. Due to
288 the low terrain gradient, a water level rise of a few centimetres is enough to
289 act as a tipping point for water to spill over certain dykes and induce several
290 hectares of additional inundated surfaces. To account for this lag time, the cor-
291 relative method for flood curves developed by [Lamagat et al. \(1993\)](#) was used
292 (see Appendix B for more details).

293 Once the delay times had been made explicit, each inundation map was
294 extracted from the time series of Sentinel-1 and 2 images and assigned a corre-
295 sponding water level. Then, a flood count and water level link parameter were
296 calculated for each pixel in the areas of interest. The approach used to achieve
297 this is depicted in Figure 9 in Appendix C. The binary flood maps - flooded
298 pixels having been assigned a value of 1 - were stacked. Subsequently, the sum
299 of times each pixel was registered as flooded was calculated. As a result, pixels
300 that represent permanent water areas, which are always detected as flooded,
301 have a flood count equal to the number of images in the analysis. Pixels on
302 elevated terrain areas that are never flooded have a flood count of zero. Next,
303 flood counts are linked to water levels measured at Koh Khel. Each pixel was
304 assigned the lowest water level (cm resolution) at which it was detected as being
305 inundated.

306 *3.4. Comparing the Flood Link With Inundation Extents Derived from Landsat* 307 *and TanDEM-X*

308 Since the link was established on the basis of relatively recent images from
309 the second half of the 2010s, it became necessary to ascertain to which extent it
310 was capable of delivering accurate estimates of inundated areas based on water
311 levels from the 1990s and the 2000s. To this end, two approaches were chosen.
312 The first was a comparison of inundation extents generated on the basis of the
313 WAFL with those directly derived from Landsat images from the period 1991-

314 2020. The second was to use the TanDEM-X (12m) Digital Elevation Model
315 (DEM), which is based on SAR imagery collected in the early 2010s, to generate
316 estimates of flood extents and compare them with those generated on the basis
317 of WAFL.

318 *3.4.1. Comparison With Landsat*

319 For the comparison with Landsat, a total of 94 optical Landsat-5 and -8
320 images were used.

321 To derive inundation maps from Landsat images, the same spectral indices as
322 for Sentinel were calculated, and the images were then partitioned into flooded
323 and dry areas by an unsupervised k-means algorithm. These maps were then
324 compared with the inundation extents generated using the WAFL and the water
325 level observed at the date the image was taken. First, the total inundated area
326 was derived for each of the 94 images and compared to the calculated inundated
327 area. Second, six Landsat images from flood seasons during the period of interest
328 (1991-2020) were chosen to identify discrepancies in spatial inundation patterns.
329 These images, at a time step of about five years, were selected because they pro-
330 vide rare cloud-free wet-season scenes. They date from 1991/11/29, 1995/11/05,
331 2000/08/31, 2005/08/21, 2013/09/12, 2015/09/11, and 2020/11/28.

332 *3.4.2. Comparison Using TanDEM-X*

333 A second method of testing the applicability of WAFL was to derive inunda-
334 tion maps from the TanDEM-X (12 m resolution) elevation model, provided by
335 the German aerospace agency (Rizzoli et al., 2017). This DEM was used to as-
336 sess the extent of inundation patterns as if they were solely linked to differences
337 in detectable terrain elevation in the study area. To establish the comparison,
338 flood extents were generated from the DEM by super-imposing a planar water
339 surface onto the DEM and classifying all areas that were beneath the elevation
340 of that surface as flooded. The planar water surface itself takes into account a
341 North-South slope, based on water level measurements at Koh Khel and in-situ
342 measurements at the western end of a Prek at the center of Zone A. Similar

343 to the Landsat measurements, a comparison of the size of inundated areas was
344 carried out, along with spatially explicit comparisons of the distribution of in-
345 undations.

346 The comparison was also performed locally, directly based on in-situ mea-
347 surements. The in-situ water level measurements were carried out using a dif-
348 ferential pressure logger (Onset Hobo MX2001), with a complete time series
349 available from September 2020 to April 2021 at 15-minute intervals. First, a
350 pseudo water level in the floodplains within a radius of 1km of the logger was
351 generated. This was achieved using inundation extents detected through Sen-
352 tinel images, and the DEM-derived elevation-area curve of the zone, and based
353 on the assumption that the water level is horizontal in such a small area (see
354 Figure 20c in Appendix D). This pseudo water level was then compared with
355 the levels measured in-situ. In reverse, the in-situ water level measurements
356 were transformed into estimates of the size of the inundated areas within this
357 1 km radius around the logger, using the same curve. Finally, the inundation
358 curves in this sub-area observed from Sentinel, and generated from WAFL and
359 TanDEM-X were compared.

360 3.4.3. Land Use Classification: Detecting Natural Vegetation

361 A final element of the applicability of the WAFL related to the detection
362 of natural vegetation in the area. Natural vegetation, such as shrubland and
363 forests, can easily obscure open water surfaces due to canopy cover, especially
364 in optical remote sensing imagery (Tsyganskaya et al., 2018; Pekel et al., 2016;
365 Plank et al., 2017). To gauge the extent of this effect on the detection of
366 inundations, an approach relying on a simple thresholding method using the
367 NDVI was chosen. The NDVI was calculated for composite Landsat images
368 for the dry seasons 1990/1991, 2000/2001, 2010/2011, and 2020/2021 for the
369 months between March and May, which are the driest in the region. Then, areas
370 exhibiting an NDVI of over 0.55 (Nath and Acharjee, 2013; Hashim et al., 2019)
371 were classified as likely forest and shrubland. Further on in the analysis, the
372 obscuring effect of canopy cover was taken into consideration by considering low-

373 lying areas classified as natural vegetation, which were otherwise surrounded by
374 open water surfaces, as likely flooded.

375 *3.5. Flood Dynamics Analysis: Calculating Inundation Durations and Inci-* 376 *dences*

377 As a next step, flood extent maps were used to generate inundation durations
378 and incidences for each pixel (10 m) in the study area for the comparison periods
379 identified on the basis of the hydrological time series. The term "inundation
380 incidence" refers to the percentage of years in each of the two comparison periods
381 during which any one pixel was flooded. Six different incidences were calculated:
382 the overall annual inundation incidence (the % of years during the period that a
383 given pixel is flooded, regardless of the date), along with inundation incidences
384 at dates of interest to agricultural practices in the area, identified on the basis
385 of interviews with stakeholders. These are the 15th of July, the 31st of July, the
386 15th of August (of importance for harvesting early wet season crops), the 31st of
387 August, and the 25th of September (of importance for rainy season cultivation
388 and planting of recession crops).

389 **4. Results**

390 *4.1. Trends and Change Points in the Water Level Time Series*

391 Detailed results of the analysis of hydrological trends and change points are
392 given in Appendix D. The statistically significant trends that could be identified
393 are highlighted in this section.

394 Generally, the water level time series at Koh Khel shows trends towards a
395 later flood rise and an earlier flood recession (the latter is significant at $p < 0.1$).
396 Most significant is the decrease of the duration of water levels at over 4 m²
397 ($p=0.022$). A break point is detected by all three homogeneity tests for the
398 hydrological year 2007/08.

²A local threshold of 4 m rather than 5 as at Neak Luong was used here because there were several years in the time series when water levels did not exceed 5 m at all.

399 The water level series at Neak Luong since 1926 exhibits significant trends to-
400 wards a later flood arrival ($p=0.03$), decreasing maximum water levels ($p<0.001$),
401 and decreasing flood durations at over 5 m ($p<0.001$). The short time series
402 (1990-2020) shows a trend towards an earlier flood recession ($p=0.06$), a shorter
403 flood duration ($p=0.09$), and especially a decreasing average water level during
404 the flood ($p=0.03$), as well as a decrease in the incidence of water levels above
405 5 m ($p=0.03$). Significant break points were detected 17 years into the time
406 series, which corresponds to the break 2009/10.

407 At both Tan Chau and Chau Doc, break points were detected for the hy-
408 drological year 2007/08. In addition, there is a significant decreasing trend in
409 terms of maximum water levels and flood durations of over 2 m at Tan Chau
410 ($p<0.001$).

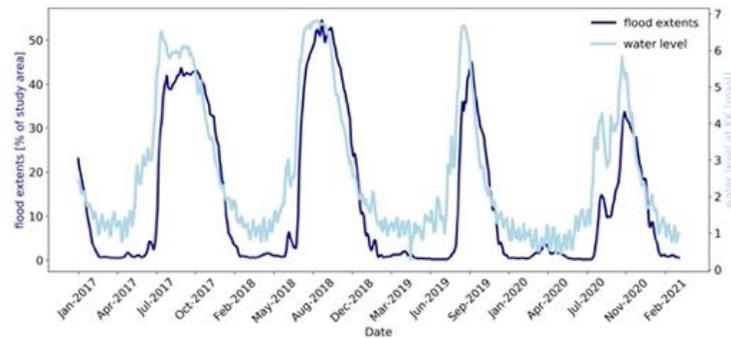
411 Overall, it emerged from the analyses that the hydrological year 2007/2008
412 significantly separates two statistically homogeneous periods characterised by
413 different flood durations, dates of flood rise and recession, and flood peaks.
414 Consequently, we used the years pre- and post-2008 as comparison periods for
415 the analysis of inundation extents reconstructed using the WAFL.

416 *4.2. Detection of Inundation Extents*

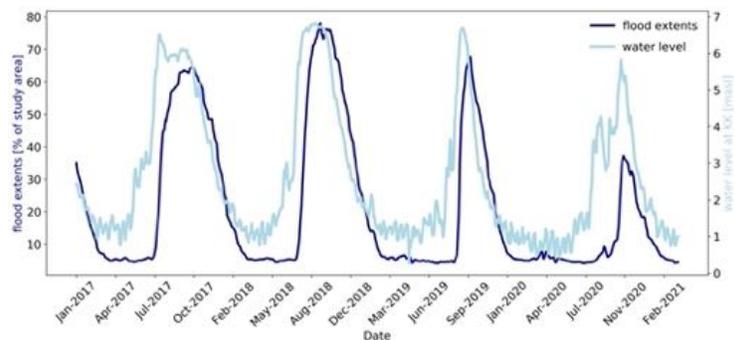
417 In total, 119 Sentinel-2 and 360 Sentinel-1 images, taken between 2017/01/01
418 and 2020/12/31 were processed. This means that, on average, one image is
419 available every three days. An example of an inundation map derived from a
420 Sentinel-2 image on the basis of the k-means classification is given in Figure 15
421 in Appendix E. The average accuracy of the classification of flooded areas lay at
422 96.5%, with a Kappa value of 0.785. Details are given in Table 3 in Appendix
423 E. However, it must be mentioned that these values at least partly result from
424 the fact that the validation data used was itself derived from remote sensing
425 imagery. Though it was set on the basis of high-resolution imagery, and with
426 first-hand knowledge of the study area in mind, the validation points were still
427 only set in unambiguous areas. Consequently, areas such as flooded vegetation
428 or inundated rice fields prior to planting that cannot be easily discriminated

429 as either flooded or not in satellite imagery are underrepresented, and their
 430 ambiguities missing from the validation results.

431 Dynamics of inundation extents in Zone A and B, detected on the basis of
 432 optical and SAR Sentinel imagery and in relation to water levels at Koh Khel,
 433 are shown in Figure 3. A good general correspondence between the dynamics of
 434 the two curves can be observed. A time delay between the dynamics of the water
 435 level curves and the response of the inundated areas can be clearly seen. Large
 436 inundated areas correspond to high water levels several days prior, justifying
 437 the use of the Lamagat model as explained in the previous section - its results
 438 are given in Appendix E in Figures 16 and 17 as well as Tables 4 and 5.



(a) Zone A



(b) Zone B

Figure 3: Dynamics of inundation extents and water levels measured at Koh Khel in the areas of interest 2017-2020.

439 *4.3. The Water Level Flood Link (WAFL)*

440 The water level flood link (WAFL) was calculated in accordance with the
441 methodology described above. It is given in Figure 4, alongside the TanDEM-X
442 elevation model. As can be seen, the WAFL shows similar elevation gradients
443 to those seen in the DEM.

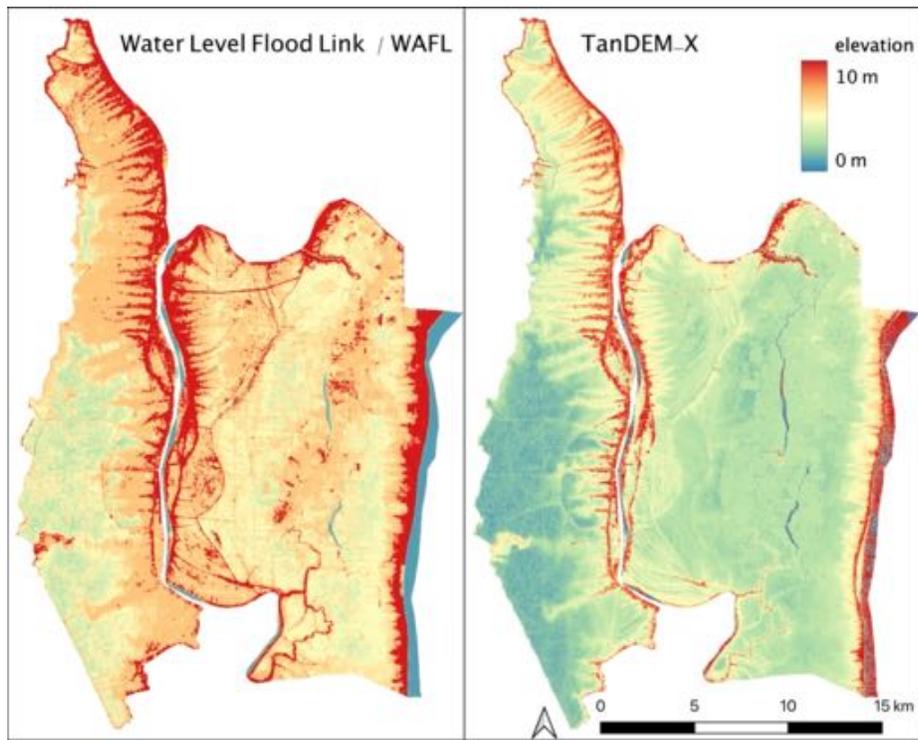


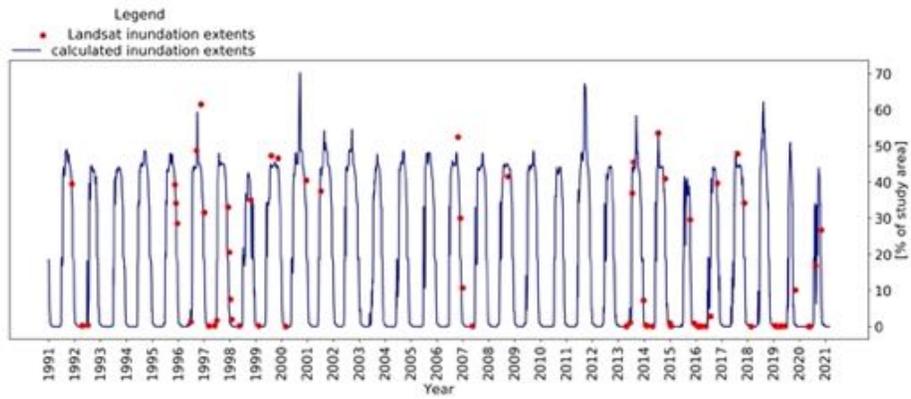
Figure 4: Side-by-side comparison of the water level at which each pixel becomes flooded, according to the WAFL, and the TanDEM-X terrain elevation model.

444 *4.4. Comparison of Calculated Inundation Extents with Flood Maps Derived*
445 *from Sentinel and Landsat and Influence of Natural Vegetation*

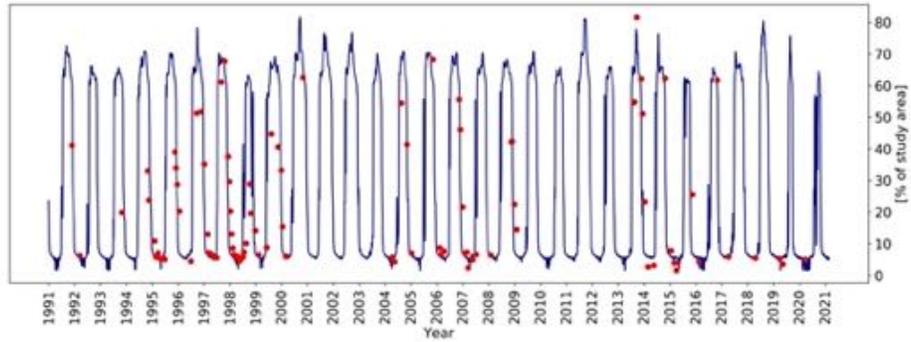
446 In terms of comparing the inundation extents calculated using the WAFL
447 with flood maps derived from Sentinel- and Landsat images, there is widespread
448 agreement, though idiosyncratic variations remain.

449 The comparison of WAFL-calculated extents with Sentinel images showed
450 an average classification agreement of 90.60% in images that were not obscured
451 by clouds (see Figure 18 in Appendix F). The agreement between the calculated
452 flood extents based on WAFL and those observed in the 94 Landsat images used
453 in this analysis is shown in Figures 5 and 6, which shows the comparison for
454 three specific dates. It emerges that in terms of overall inundated areas, there is
455 a strong agreement between the two methods. As Figure 5 shows, there are some
456 deviations in years that saw heavy floods, during which calculated inundation
457 extents are lower than those obtained through Landsat classification.

458 In addition, it can be noted that the spatial distribution of inundations
459 varies between the two methods of detection and that the deviations are more
460 extensive the further back in time the points of comparison lie. For example,
461 Figure 6 shows that WAFL-derived inundation maps detect extensive inundated
462 areas in Zone B in the 2010s, while these areas are dry according to the Landsat
463 classification. In contrast, areas of medium elevation in Zone A (transition zones
464 between Boeung and Chamkar) appear as flooded in the 1990s and early 2000s
465 in Landsat images, but are registered as dry by WAFL. The strong agreement
466 between the total water surfaces obtained by the two methods may thus be
467 contingent. This hypothesis will be further investigated in the discussion section.



(a) Zone A



(b) Zone B

Figure 5: Comparison of inundated areas - time series derived from the WAFL, and individual Landsat-5 and -8 images

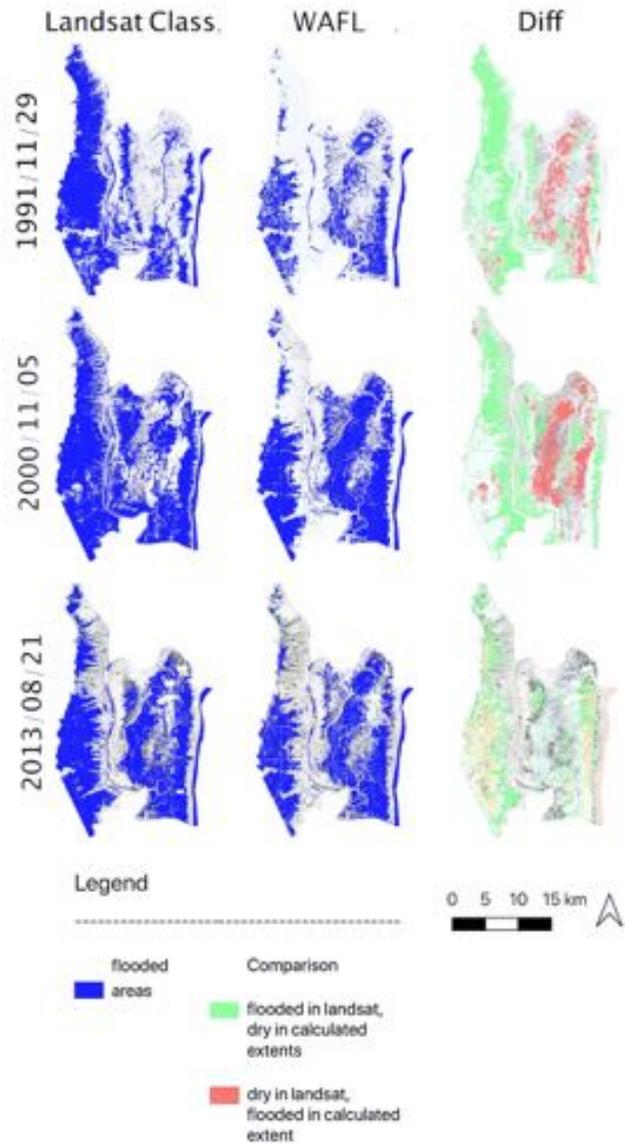


Figure 6: Comparison of inundation extents derived from the WAFL and Landsat-5 and -8 images

468 The analysis of the extents of natural vegetation indicates that extensive
 469 areas of shrubland and regularly flooded forests were present in Zone B in the

470 1990s, but that they shrunk to a fraction of their former size by 2020 due to
471 large-scale conversion to rice fields. The decrease between 1990 and 2000 is
472 limited, at ca. 2% of the overall area (see Figure 19 in Appendix F). After that,
473 there is a sharp decline: -42% and -62% by 2010 and 2020 when compared to
474 1990. Such findings are supported by interview data.

475 In Zone A, the development is different. Here, natural vegetation detected in
476 the early 1990s is located in the southwestern part of the study area. This patch
477 of vegetation decreased considerably between 1990 and 2000 - by 64% in fact -
478 due also to conversion to rice fields. After that, the overall extents of detected
479 natural vegetation rebounded and even gained 20% in area in comparison to
480 1990. However, the increased extent of the detected natural vegetation is more
481 likely to be due to the planting of fruit trees such as mango, whose areas,
482 according to interviews and agricultural statistics, have sharply increased over
483 the last 10 years.

484 Furthermore, the analysis of the extents of natural vegetation shows that
485 there is an extensive overlap between those areas that are detected as flooded in
486 WAFL-derived maps, but not by those generated directly from Landsat images.
487 The Overlap line of Table I shows that upwards of 93% of pixels that exhibit
488 these discrepancies coincide with the detected extents of natural vegetation.
489 This indicates that these areas may be flooded but their water surface masked by
490 canopy cover and hence not detected by Landsat imagery. If one considers that
491 all forest pixels that overlap with areas being detected as dry by Landsat and wet
492 by the WAFL are indeed flooded, agreement scores between the two methods
493 for detecting flood extents increase from an average of 79.75% to 87.16% for
494 Zone A, and from 68.49% to 87.18% for Zone B.

	Zone	1991	1995	2000	2005	2013	2015	2020
Agreement between LS and WAFL [% of study area]	A	67.64	68.85	74.98	81.85	85.68	85.87	93.37
	B	72.25	49.14	57.49	53.08	78.35	78.00	91.11
LS Wet - WAFL Dry [% of study area]	A	25.83	16.14	20.03	8.71	6.09	8.41	4.37
	B	6.93	14.68	19.76	11.06	8.9	20.13	7.37
LS Dry - WAFL Wet [% of study area]	A	6.53	15.00	4.99	9.44	8.22	5.72	2.25
	B	20.82	36.19	22.75	35.87	12.75	1.86	1.50
Overlap of LS dry area with forest [% of dry area]	A	99.93	99.93	99.93	99.93	97.09	99.93	99.89
	B	99.97	99.97	99.97	99.97	93.42	99.95	99.96
Corrected agreement [% of study area]	A	74.17	83.84	79.97	91.28	93.66	91.59	95.62
	B	93.06	85.32	80.23	88.94	90.26	79.86	92.61

Table 1: A comparison of the agreement and discrepancies between the WAFL-derived inundation extents (WAFL) and the Landsat-derived flood maps (LS).

495 *4.5. Comparison of Calculated Inundation Extents with Flood Maps Derived*
496 *from TanDEM-X*

497 When it comes to the flood extents derived from TanDEM-X and their com-
498 parison with the inundation maps created using the WAFL, several salient points
499 can be observed.³ The comparison between TanDEM-X derived inundation
500 maps in the 1-km radius around the in-situ sensor in Zone A and direct inunda-
501 tion observations from Sentinel images reveals a very good correspondence (see
502 Figure 21 in Appendix F). Some hydraulic elements, like dykes, do not appear
503 in TanDEM-X. This leads to an overestimation of flooded areas with the DEM
504 compared to WAFL. We can also expect that these elements slow the filling
505 of the area, introducing some delay between the water level measured at the
506 sensor and the response in terms of inundations.⁴ In addition, it emerges that
507 the WAFL underestimates flood extents in this particular part of the study area
508 in comparison to both the Sentinel-derived flood extents and those calculated
509 from the TanDEM-X.

510 At a larger scale, the quality of this correspondence decreases, which illus-
511 trates the limitation of the DEM (especially to capture hydraulic connections
512 and barriers) and of the assumption of a planar water surface. We can also

³See Figure 20 in Appendix F for the elevation-area curves extracted from TanDEM.

⁴This can be observed in Figures 22a and 22b in Appendix F, which show a lag time of a few days between the two curves.

513 expect errors due to propagation times not being evenly distributed throughout
514 the area.

515 The water level at which pixels become flooded according to the WAFL is
516 generally higher than their elevation in the TanDEM-X model (see Figure 4).
517 The exception to this is the center of Zone B. Here, the WAFL shows some
518 areas that become flooded at higher water levels than the surrounding terrain,
519 while the TanDEM-X registers continually low elevations.

520 As a consequence of this discrepancy between the WAFL and TanDEM-X
521 elevations, TanDEM-X-derived flood extents are generally higher than those
522 calculated using the WAFL (see Figure 7), even when taking into account a
523 North-South slope of the water surface area.

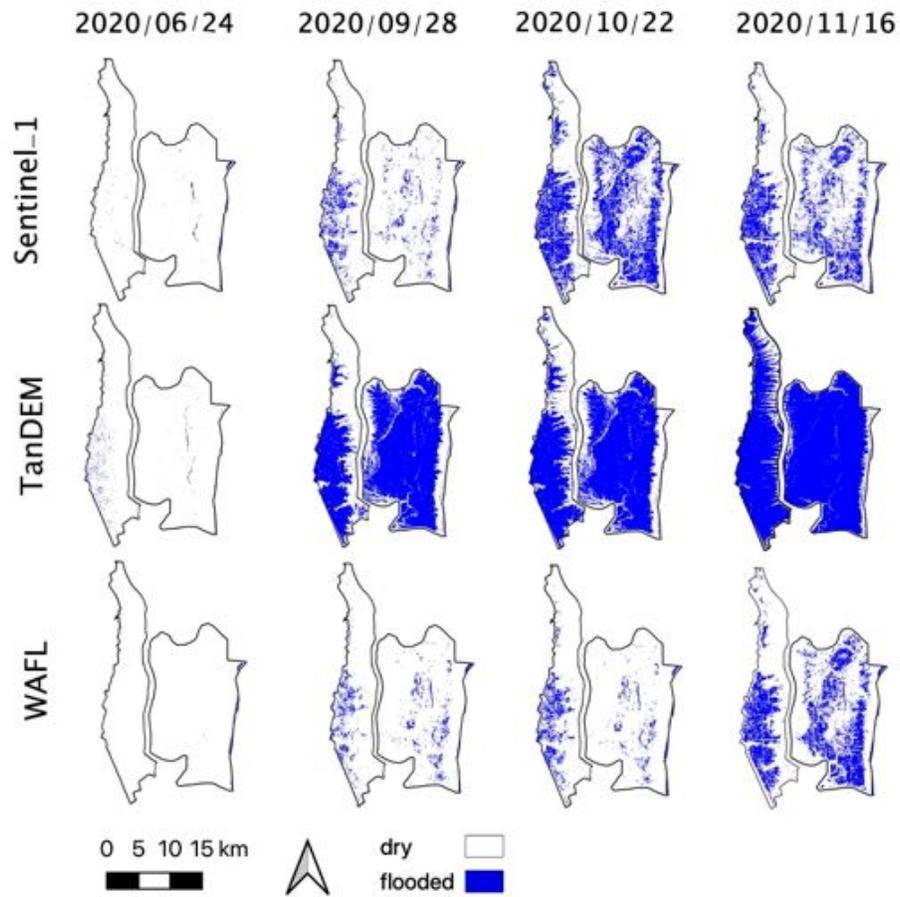


Figure 7: Comparison of inundation extents derived from TanDEM-X, and calculated from the WAFL, and as observed from Sentinel-1 for four dates during the 2020 flood season.

524 4.6. *Changes in Inundation Incidence, Durations, and Patterns Pre- and Post-*
 525 *2008*

526 When the WAFL is applied to the entirety of the water level time series
 527 to generate inundation maps, several trends emerge for the comparison periods
 528 1991-2008 and 2009-2020. These trends are summarized in Table 2. It emerges
 529 that average annual inundation durations in both zones have decreased. In some
 530 areas of both zones, this decrease is as much as 39 days when the two periods
 531 are compared. In Zone A, the average decrease, at 15 days, was lower than in

532 Zone B, at 23 days.

533 As for inundation incidence, a similar overall declining trend can be noted.
 534 However, the magnitude of this decline is unevenly distributed across the flood
 535 season. Overall, there is a sharp decrease in inundation incidence in July and
 536 early August in both Zone A and B. In Zone A, the largest mean decrease, at
 537 -20% of years per period, can be observed in late July. In Zone B, this is the case
 538 for mid-August, at -23%. In contrast, the decrease in mean inundation incidence
 539 is limited in late September, a time at which the flood peak would traditionally
 540 have occurred already. At this time, the average inundation incidence remains
 541 unchanged in Zone B, and only declines by -8% in Zone A. On an annual basis,
 542 the decline in inundation incidence is much larger in Zone B, at -6% than in
 543 Zone A at -2%.

Parameter	Pixel-based changes in inundation incidence [% of years/period]						Changes in inundation duration [days]	
	Jul 15	Jul 31	Aug 15	Aug 31	Sep 25	Overall		
Zone A	Max +	5	5	5	20	15	12	4.81
	Mean	-19	-20	-18	-16	-8	-2	-15.21
	Max -	-53	-41	-64	-33	-38	-25	-39.25
Zone B	Max +	5	5	5	15	15	12	5.17
	Mean	-13	-11	-23	-7	0	-6	-22.97
	Max -	-51	-48	-43	-35	-38	-30	-39.14

Table 2: Average changes in inundation incidence and durations in Zone A and B pre- and post-2008 for individual pixels. Given are the largest increase in flood incidence and duration for any individual pixel in the study area (Max +), the largest decrease for the same (Max -), as well as the average change in incidence and duration across all pixels in the study area.

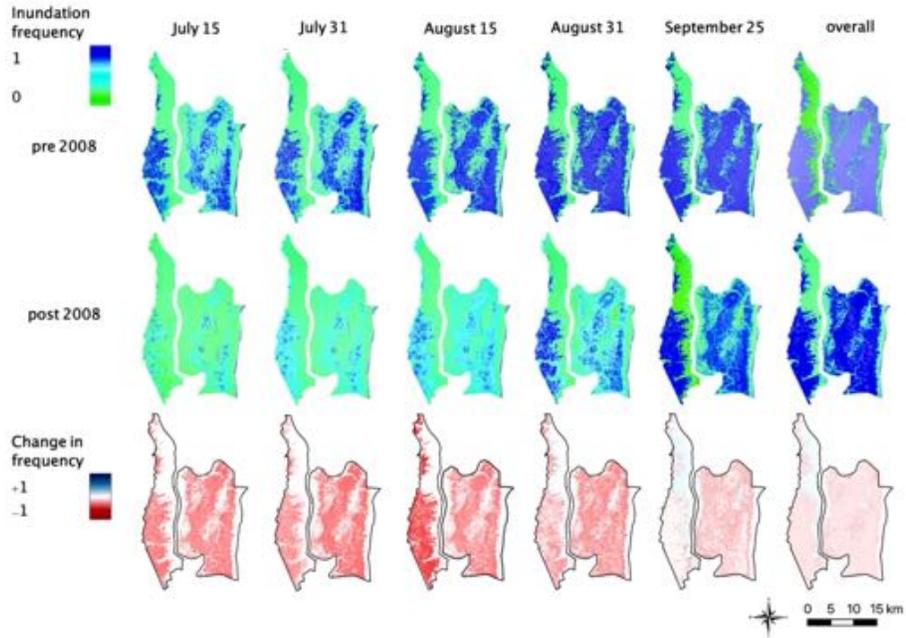


Figure 8: Visual comparison of inundation incidences pre- and post-2008

544 **5. Discussion**

545 *5.1. Local Hydrological Trends and their Reflection of Basin-Wide Changes*

546 Hydrological trends in the Cambodian upper Mekong delta closely mirrored
 547 those observed in basin-wide studies, with shorter flood durations and lower wet
 548 season water levels. Furthermore, the division of comparison periods into a pre-
 549 and post-2008 series mirrors the break point found in basin-wide studies, such
 550 as Yun et al. (2020) and Heng et al. (2021).

551 *5.2. Inundation Mapping Using Sentinel: Between Biases and the Value of Ob-*
 552 *serving Local Dynamics*

553 In terms of inundation dynamics, curves of flood extents closely correspond
 554 to those of locally measured river water levels, both for Zone A and B. The
 555 most noticeable difference between the two zones is that the delay time between
 556 the two curves is longer for Zone B than for Zone A, which may be due to its

557 larger width, as well as the relatively shorter length of the Preks connecting the
558 river to the floodplains. In combination, these terrain characteristics mean that
559 floods take longer to reach the center of Zone B than of Zone A.

560 *5.3. Validity of the WAFL: Balancing Natural Vegetation, Sedimentation, and* 561 *Terrain Correspondence*

562 The comparison between WAFL-derived inundation extents and flood maps
563 extracted from Sentinel-2 imagery reveals several advantages and drawbacks of
564 the proposed methodology. The benefit of using the WAFL-reconstructed in-
565 undation extents are best exemplified in the case of the image taken during the
566 2018 flood season, shown in Figure 18 in Appendix F. The optical Sentinel-2
567 images at this date show several gaps, left by cloud masking. However, not all
568 clouds were properly detected by the masking algorithm and those that remain
569 are falsely classified as dry areas in the Sentinel-derived flood map, leading to
570 inconsistencies with the WAFL classification. The drawbacks of the methodol-
571 ogy are most clearly revealed in the image from the 2020 flood season. Here,
572 it is visible that the agreement of the two flood classifications is considerably
573 higher in Zone A than in Zone B. Particularly, the WAFL classification in Zone
574 B fails to capture some of the areas detected as inundated in the Sentinel-2
575 images. This may be due to the fact that water level dynamics in this year
576 deviated considerably from the previously observed norm, with an early peak
577 followed by a lowering of levels, before abruptly rising again towards the season's
578 main peak. It can be conjectured that the correlative relationship established to
579 characterise the delay time between water levels and the response of inundated
580 areas failed to adequately capture this development. Whether this is an isolated
581 response is hard to assess, since similar early peaking patterns cannot be found
582 anywhere else in the data.

583 In terms of which factors most impact the detection of floods and the appli-
584 cability of the WAFL, natural vegetation emerges as the central element in the
585 comparison with Landsat images. This is particularly apparent as the binary
586 classification into flooded and not flooded areas that was chosen in this approach

587 limits the possibility of detecting flooded vegetation. Overall, the comparison
588 with Landsat-derived inundation maps highlights the potential of the WAFL for
589 re-constructing past inundation extents. In general, while the WAFL also has
590 some issues mistaking areas with natural vegetation for dry areas, even when
591 they are flooded, this misclassification is much less frequent than with Landsat.
592 There are two main reasons for that. First, Sentinel-1 SAR (on the basis of
593 which the WAFL was derived) has the capacity to detect water under vegeta-
594 tion layers (Tsyganskaya et al., 2018). And second, at the time the Sentinel
595 images were recorded (2017-20) there was already much less natural vegetation
596 in the study area than at the time that many of the Landsat images used in
597 this study were taken (cf. Figure 19 in Appendix F).

598 A second discrepancy in the comparison with Landsat is observed on higher-
599 lying terrain in the study area. Here, Landsat continually registers inundations
600 in the 1990s and early 2000s, which the WAFL fails to capture. That may be
601 due to the fact that at the time that the Landsat images were recorded, these
602 areas actually were flooded regularly, but that by the time the Sentinel images
603 were taken, this had changed. Some possible explanations for that could be the
604 construction of local infrastructure (such as small dams and dykes), the natural
605 deposition of sediments, or the raising of land through geotechnical projects
606 (it is not rare to see farmers raising the level of their land to build houses or
607 plant trees). The regular distribution of this discrepancy in flood prevalence
608 between Landsat and WAFL-derived maps seems to speak more for the second
609 option. In terms of sediment deposition on the floodplains of the Mekong delta,
610 Hung et al. (2014) found an average annual deposition of 6.86 kg/m² in the
611 Vietnamese Mekong delta in Tam Nong district in Dong Thap province. This
612 corresponds to an annual increase of 6 mm in height. These deposition rates are
613 likely to be higher on the Cambodian side of the border due to the absence of
614 dams and dykes. According to Manh et al. (2014), deposition on the Cambodian
615 floodplains is indeed up to six times higher than in Vietnam, ranging from 19 to
616 23% of the annual sediment load at Kratie, rather than the 1 to 6% deposited
617 in the compartmentalised floodplains in Vietnam. However, this also highlights

618 one of the principal limitations of WAFL - that it uses recent data to re-construct
619 past inundation extents. As the conjectured effect of sedimentation shows, this
620 may lead to errors where terrain configuration has changed significantly over the
621 past decades. As the likelihood of such significant changes invariably increases
622 over time, this necessarily means that the likely robustness of WAFL-derived
623 maps diminishes the further back in time it is applied.

624 When it comes to the comparison of the WAFL with TanDEM-X and the
625 inundation extents derived on both bases, using a planar water surface super-
626 imposed on the DEM on the basis of in-situ water levels, seems to be a valid
627 approach on a local scale. From a physical perspective, it appears that the
628 water level registered by the logger could be construed to represent the inflow
629 into the Boeung area, while the pseudo water level derived from Sentinel can be
630 seen as the storage response, with local hydrological processes mirroring the dy-
631 namics of those of a reservoir (the Boeung) filling and emptying. This is typical
632 for flood storage cells: the inflow-outflow is governed by the difference in levels
633 between the main connection point and the mean level in the area. The delay
634 is directly linked to the volume of water stored in the considered area and the
635 flow rate. When there is no obstacle in the considered area, the delay is very
636 short and water level can be considered as horizontal (propagation effects are
637 not visible at a daily time step). When dykes limit the flow propagation, the
638 filling of the area is made possible by small openings in dykes (usually made by
639 farmers to irrigate their rice fields). Then it takes a longer time to fill the area.
640 During flood recession, the processes are inverted: water level decreases rapidly
641 in the Preks that are well-connected to the Bassac, while water is stored in the
642 floodplains. Water is kept as long as possible in rice fields (by clogging the
643 dykes) and recedes progressively by gravity (surface and subsurface drainage)
644 and evapotranspiration.

645 However, the robustness of this approach diminishes considerably when ap-
646 plied at the scale of the entire study area. At this scale, the assumption of
647 a horizontal water surface slope no longer holds. Even when superimposing
648 a sloped water surface over the entire DEM and taking into account correla-

649 tions between the station at Koh Khel and the logger, the discrepancy remains
650 high due to the complexity of the hydrological processes in the area. Broadly,
651 this leads to an overestimation of inundated extents derived from TanDEM-X.
652 However, the use of the DEM does have the advantage of absolutely removing
653 the interference of natural vegetation, as evidenced by the discrepancies in the
654 center of Zone B observed in Figure 7.

655 *5.4. Decreasing Flood Incidence and Durations in the Cambodian Mekong Delta:* 656 *Patterns and Impacts*

657 Despite limitations in the detection of the full flood extents in the 1990s and
658 early 2000s, the analysis clearly shows a pronounced decrease in the incidence
659 and duration of floods, especially in July and the first half of August. Large
660 swaths of the study area, which were regularly flooded during these months in
661 the 1990s, now remain dry until the second half of August. Taken together with
662 the trends of earlier flood recession and the shorter flood durations outlined
663 above, this means that overall, inundations in the Cambodian Mekong delta
664 arrive later and recede earlier.

665 To a certain extent, this is in line with previous basin-wide studies such
666 as Yun et al. (2020) and Hecht et al. (2018) that investigated the impacts of
667 climate change and hydropower development. Their main findings were that
668 a lower wet season discharge was to be expected in the future as a result of
669 these developments, along with a higher dry season discharge. In terms of
670 inundations, however, these higher dry season discharges do not balance the lack
671 of inundations during the wet season that are key for the ecological functioning of
672 the floodplains. Similarly, the results are in line with observations by Aires et al.
673 (2020), who found a declining trend in inundation extents in their analysis of the
674 Vietnamese and Cambodian Mekong delta using MODIS data. The same study
675 also found inundations to be delayed by about two weeks in the Cambodian
676 part of the Mekong delta. The present study indicates a longer delay, which
677 may be due to differences in both the time frame and the spatial resolution of
678 the data used. Figure 8 indicates that the incidences with which pixels were

679 flooded in late July prior to 2008 are now only attained in late August or early
680 September. Similar parallels exist in the work of [Heng et al. \(2021\)](#). In their
681 modelling study of the Cambodian floodplains - one of the few taking this region
682 as its focus - the authors conclude that total flood extent is projected to decline
683 by 18% by 2040.

684 Overall, the alterations outlined above are anathema to the formerly pre-
685 dictable hydrological regime of the region, and are likely to have wide-reaching
686 consequences for agriculture and fisheries. Greater variability in the dates of the
687 flood arrival and its recession may, for instance, result in shifts in the planting
688 and harvesting times for recession crops and an increased need for irrigation wa-
689 ter ([Erban and Gorelick, 2016](#)). As far as fisheries are concerned, the later onset
690 of floods and overall decrease in inundation durations limit the period during
691 which fish populations can regenerate in the shallow waters on the floodplains
692 ([Hortle, 2009](#)). Compounded with the decrease in natural vegetation, which
693 provides valuable structural habitat features, this is likely to negatively impact
694 fish population dynamics. [Vu et al. \(2021\)](#) showed a close correlation between
695 the long-term decline in commercial fish catches and declining peak water levels
696 in the Mekong delta. Furthermore, local-level data obtained by the authors
697 from fishermen in the area show fish catch to be much lower in years when the
698 water level at Koh Khel exceeds 4 m for a lower number of days. These changes
699 in inundation extents and durations are likely to impact food security in the re-
700 gion. [Burbano et al. \(2020\)](#), for example, link the shorter flood durations in the
701 Tonle Sap region and the Mekong delta floodplains to shifts in dietary protein
702 from fish to meat, and, consequently, land use changes resulting from the need
703 to accommodate cattle.

704 Shorter inundation durations and lower incidence also reduce the spatial
705 and temporal extent of the terrestrial-aquatic interface that many regulating
706 ecosystem services depend on. This includes processes such as pest regulation,
707 nutrient deposition, and soil and ground water recharge ([Brown and My Phung,](#)
708 [2010](#); [Chen et al., 2011](#)).

709 Furthermore the analysis also shows that, even though large changes have

710 occurred in the basin over the past three decades, the link between river water
711 levels and inundation extents has remained relatively static. In contrast to the
712 major changes in the hydrology of the Mekong river, its hydraulic connections to
713 its Cambodian floodplains seem to have changed comparatively little, which may
714 be related to the still limited development of water control infrastructure in the
715 region. At this point, it is important to note the fact that the results presented in
716 this study partially mirror those from analyses of basin-wide trends in discharge
717 and water levels because the WAFL has been constructed on the basis of these
718 water levels. The merit of the study, though, lies in illustrating the magnitude
719 of these parallelisms, which depends on the unique terrain configuration of the
720 floodplain and the hydraulic controls that determine the dynamics of inundation
721 processes.

722 *5.5. Generalizability and Transferability to other Case Study Areas*

723 As stated above, the ultimate aim of the developed methodology is to provide
724 long-term insights into the spatial dynamics of inundations in tropical deltas.
725 Applying the approach to the Mekong delta showed that this is possible with ac-
726 ceptable average accuracies of 87% in comparison to historical inundation maps
727 derived from Landsat. Such comparisons have also highlighted the limitations of
728 the WAFL with regard to long-term changes in local terrain configuration, and
729 the challenges posed by LULC characteristics such as the presence of natural
730 vegetation.

731 For an application in other study areas, this means that a basic knowledge
732 of changes in local conditions is a prerequisite for the development and applica-
733 tion of the WAFL. An awareness of landcover dynamics - which can be assessed
734 through historical LULC analysis - or significant shifts in terrain elevations and
735 the river-floodplain connections, notably due to the construction of water con-
736 trol infrastructures, is crucial. It must also be noted that the WAFL is primarily
737 applicable in areas where inundations are correlated largely with dynamics in
738 river water levels. This refers to areas in which the influence of local precipita-
739 tions and groundwater is limited and where there are few obstacles to the flow

740 of water into and out of the floodplain. This can be mostly the case in semi-arid
741 places but also in tropical areas like in the Mekong delta, as demonstrated in
742 this study by the comparison of water level dynamics and Sentinel-derived inun-
743 dation extents. Where historical records of water levels are available, as a first
744 step in the application of WAFL, such an analysis should be used to elucidate
745 the applicability of the methodology. However, in areas where inundations are
746 significantly correlated with processes such as local precipitation or groundwa-
747 ter logging, adjustments to the correlation model can be made by introducing
748 new input variables, provided time-series are available.

749 **6. Conclusion**

750 This paper offers an innovative approach, combining multiple methods and
751 types of data, to elaborate a water level-flood link (WAFL) on the basis of
752 which past daily inundation extents can be reconstructed, as illustrated for the
753 Cambodian upper Mekong delta with a time series starting in 1991. Combining
754 remote sensing and statistical methods with an in-depth knowledge of hydro-
755 logical processes and agricultural dynamics of the Cambodian upper Mekong
756 delta acquired over several years of research makes it possible to surmount bar-
757 riers posed by the paucity and heterogeneity of data in this region, and attain
758 a better understanding of changes in inundation dynamics.

759 The water level - flood link (WAFL) is established on the basis of Sentinel-1
760 and 2 data collected between 2017 and 2020 and in-situ hydrological measure-
761 ments. Its robustness is further tested through a comparison with Landsat-
762 derived inundation maps and inundation extents calculated on the basis of
763 TanDEM-X. The results show that the WAFL is capable of acceptably rep-
764 resenting past flood extents. For one thing, it has a smaller propensity for
765 mistaking flooded vegetation for dry areas than inundation maps derived from
766 Landsat images. For another, it is based on actual physical observations and
767 thus avoids overestimating inundation extents, a pitfall to which flood maps
768 derived from superimposing a sloped water surface on TanDEM-X are prone.

769 Nonetheless, it must be noted that due to long-term changes in terrain config-
770 uration due to sedimentation, and the construction of local infrastructure, the
771 robustness of the method diminishes the farther back in time it is applied. In
772 terms of improving the approach, it is possible to envision an additional layer
773 of correction of the Sentinel-derived maps on the basis of TanDEM-X to remove
774 any remnants of vegetation interference, as well as the improvement of the wa-
775 ter surface slope on the scale of the floodplains. Furthermore, a spatialisation
776 of delay times could lead to more regionally adapted results. And finally, a
777 correction based on long-term sedimentation rates is conceivable.

778 In the case study area in the Cambodian Mekong delta, the results show
779 a small decrease in overall inundation incidence as well as a sharp decrease
780 in inundation incidence at specific dates in July and the first half of August.
781 The results furthermore indicate that inundations duration are on average 19
782 days shorter in the period 2008-2020 than in the period 1991-2008. Overall,
783 this is likely to have considerable adverse impacts on agricultural cycles, fish
784 reproduction, and regulating ecosystem services such as soil and ground water
785 recharge.

786 Considering all the limitations outlined above, the WAFL offers a valuable
787 path to reconstructing a consistent time series of inundation extents going back
788 to the 1990s. For the purpose of assessing long-term changes in spatial inunda-
789 tion patterns this is invaluable - especially considering the alternatives of having
790 only sparse amounts of contemporary optical data, data with insufficient spatial
791 and temporal resolution, or no spatial data at all. The WAFL methodology is
792 applicable to other similar areas in large floodplains, where inundated areas are
793 directly correlated to the water level at a gauging station through hydraulic
794 processes and where historical water level data is available. In some areas, how-
795 ever, long-term shifts and precipitation contributions may require some further
796 developments to improve the methodology.

797 **Declaration of Competing Interest**

798 The authors declare that they have no known competing financial interests or
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818 **References**

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1144 **Appendix A: Explanation of the Choice of Hydrological Parameters**
1145 **Chosen for Analysis**

1146 These parameters reflect the immediate considerations of farmers with re-
1147 gard to their cultivation practices. The date of the flood arrival, for example,
1148 determines whether early wet season crops can be harvested in time, or whether
1149 they will suffer damage from the oncoming inundations. Similarly, the date of
1150 the flood recession dictates when crops can be planted on the formerly unin-
1151 dated fields and the extent to which they will depend on irrigation at the end
1152 of their growing cycle. The dates of the flood rise and recession - and thus the
1153 overall flood duration - were defined on the basis of the rate at which water
1154 levels rise and fall (Δw_l). The date of the largest positive Δw_l was taken as the
1155 start of the flood, the date of the largest negative Δw_l as the date of recession.
1156 The number of days between these two dates was taken as the flood duration.
1157 Local water level thresholds were chosen on a qualitative basis, based on con-
1158 versations with stakeholders. They reflect water depths that are conducive to
1159 fish reproduction and that farmers feel allow cultivation without constituting
1160 potential threats to harvesting.

1161 **Appendix B: The Lamagat Correlation Model**

1162 Initially developed to identify correlations between gauging stations, the
1163 Lamagat approach has been used with satellite data series in both the Tana
1164 river delta in Kenya by [Leauthaud et al. \(2013\)](#), and at the Niger and Senegal
1165 rivers by [Bader et al. \(2016\)](#) (flooded areas) and [Belaud and Bercher \(2010\)](#)
1166 (satellite altimetry). It was developed to model the propagation of flood waves,
1167 specifically in areas with low slope gradients and observable hysteresis effects in
1168 rating curves - such as deltaic floodplains. This approach combines kinematic
1169 elements with statistical methods. Its main advantage is that it identifies opti-
1170 mal correlation factors not between the overall time series of flood extents and
1171 water levels in the river, but between a set number of sub-sections of the time
1172 series. Consequently, it can account for the varying time delays depending on

1173 the phase of the flood cycle. Therefore, the time delay is expressed as a function
 1174 of the river water level, while the flood extent at a given time is a function of
 1175 the water level observed some days before.

1176 **Appendix C: Visual Representation of WAFL Calculation**

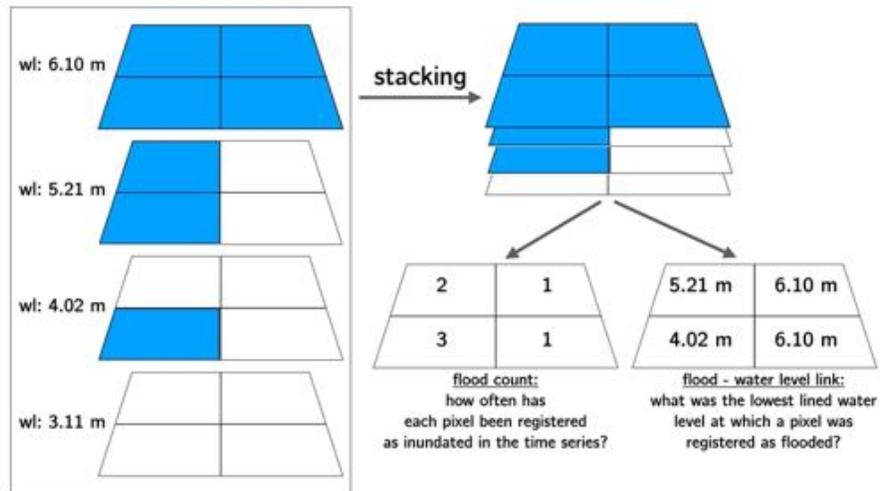
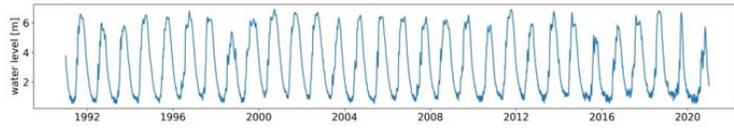
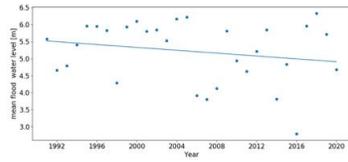


Figure 9: Logic workflow for creating the water level - flood link (WAFL). Example of an area with 4 pixels, and 4 images corresponding to 4 different water levels at Koh Khel. Blue areas represent flooded pixels.

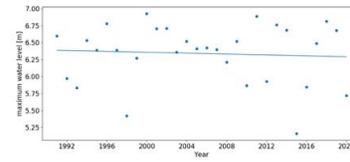
1177 **Appendix D: Results of the Hydrological Analysis**



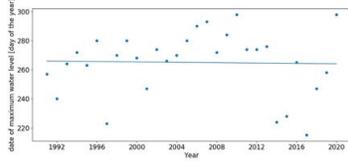
(a) Water levels at Koh Kehl 1990-present.



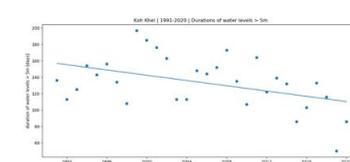
(b) Mean flood water levels at Koh Kehl.



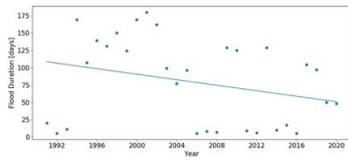
(c) Maximum water level at Koh Kehl.



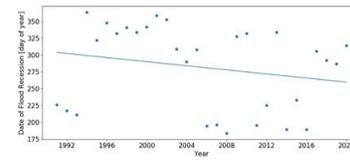
(d) Date of maximum water level at Koh Kehl.



(e) Flood duration over 4 m at Koh Kehl.

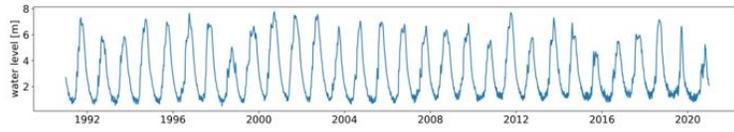


(f) Overall flood duration at Koh Kehl.

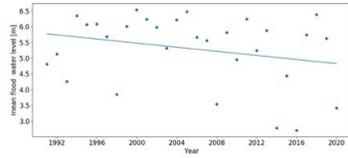


(g) Date of flood recession at Koh Kehl.

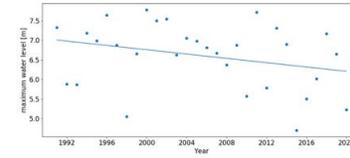
Figure 10: Results of hydrological analysis at Koh Kehl.



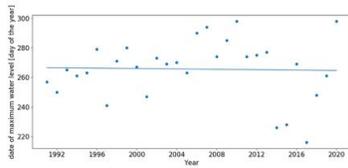
(a) Water levels at Neak Luong 1990-present.



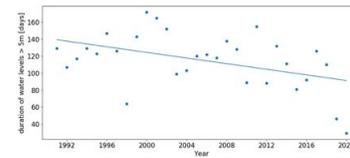
(b) Mean flood water levels at Neak Luong.



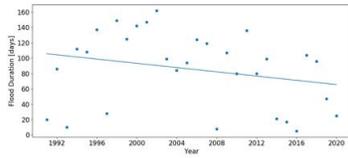
(c) Maximum water level at Neak Luong.



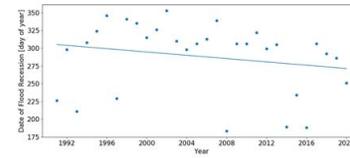
(d) Date of maximum water level at Neak Luong.



(e) Flood duration over 5 m at Neak Luong.

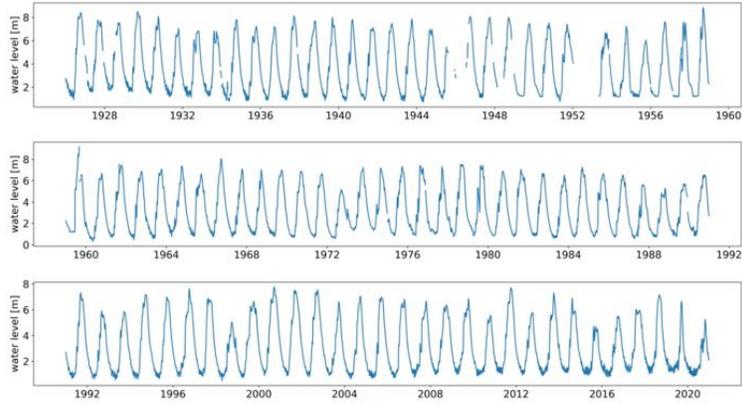


(f) Overall flood duration at Neak Luong.

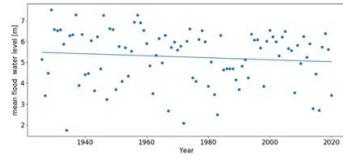


(g) Date of flood recession at Neak Luong.

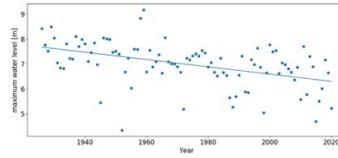
Figure 11: Results of hydrological analysis at Neak Luong, short time series.



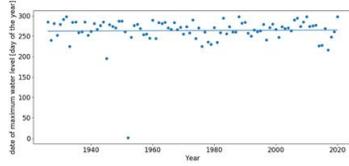
(a) Water levels at Neak Luong 1926-present.



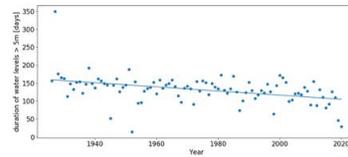
(b) Mean flood water levels at Neak Luong.



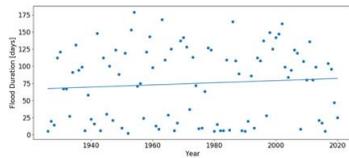
(c) Maximum water level at Neak Luong.



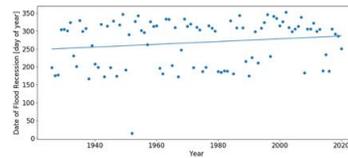
(d) Date of maximum water level at Neak Luong.



(e) Flood duration over 5 m at Neak Luong.

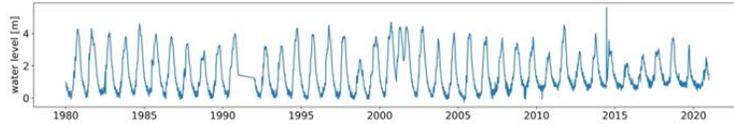


(f) Overall flood duration at Neak Luong.

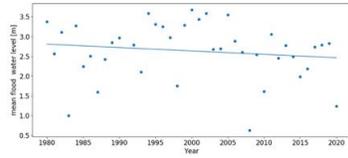


(g) Date of flood recession at Neak Luong.

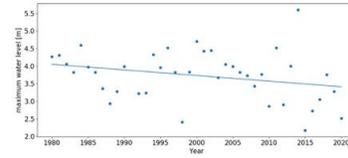
Figure 12: Results of hydrological analysis at Neak Luong, long time series.



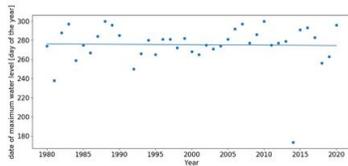
(a) Water levels at Tan Chau 1980-present.



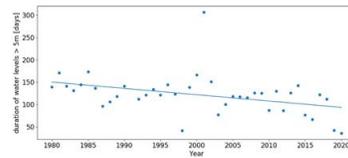
(b) Mean flood water levels at Tan Chau.



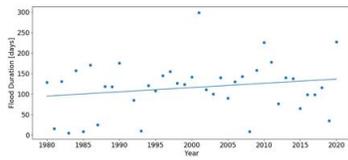
(c) Maximum water level at Tan Chau.



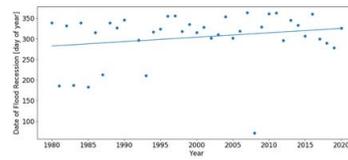
(d) Date of maximum water level at Tan Chau.



(e) Flood duration over 2 m at Tan Chau.

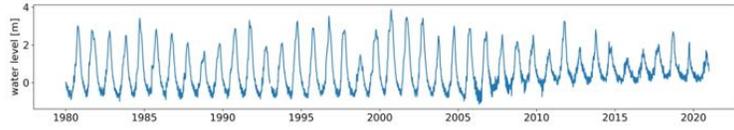


(f) Overall flood duration at Tan Chau.

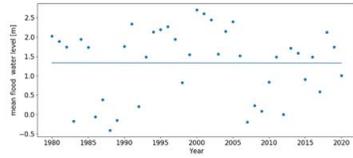


(g) Date of flood recession at Tan Chau.

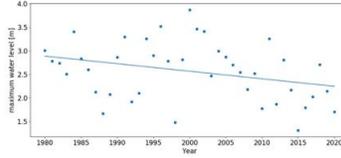
Figure 13: Results of hydrological analysis at Tan Chau.



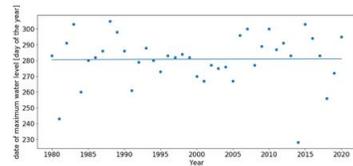
(a) Water levels at Chau Doc 1980-present.



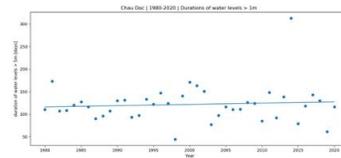
(b) Mean flood water levels at Chau Doc.



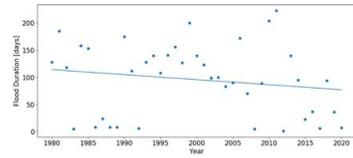
(c) Maximum water level at Chau Doc.



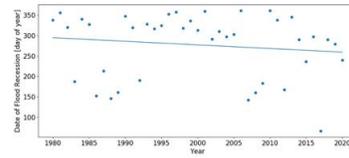
(d) Date of maximum water level at Chau Doc.



(e) Flood duration over 2 m at Chau Doc.



(f) Overall flood duration at Chau Doc.



(g) Date of flood recession at Chau Doc.

Figure 14: Results of hydrological analysis at Chau Doc.

1178 **Appendix E: Results of the Detection of Inundation Extents Using**
 1179 **Sentinel 1 and 2 and the Lamagat Correlation**

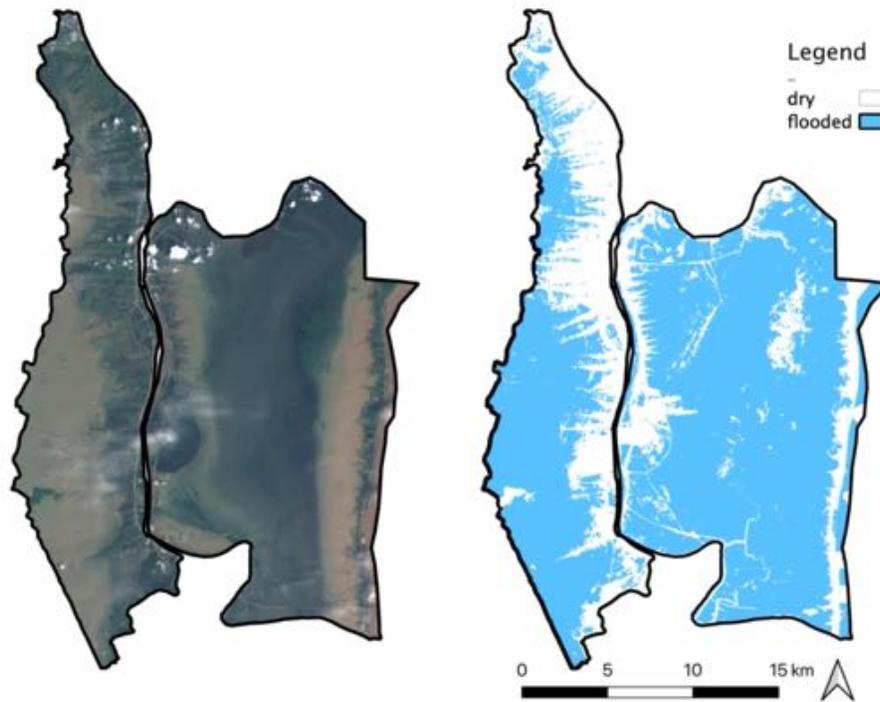


Figure 15: Example of classification using k-means and optical Sentinel data on 2018-10-01

Validation Date	Overall Accuracy Optical	Overall Accuracy Radar	Kappa Optical	Kappa Radar
2017-01-29	0.994	0.984	0.948	0.83
2018-06-24	0.938	0.979	0.757	0.908
2019-09-27	0.993	0.997	0.945	0.993
2019-08-14	0.917	0.917	0.526	0.371
Average	0.961	0.965	0.794	0.776

Table 3: Accuracy assessment of the inundation classification using Sentinel-1 and 2

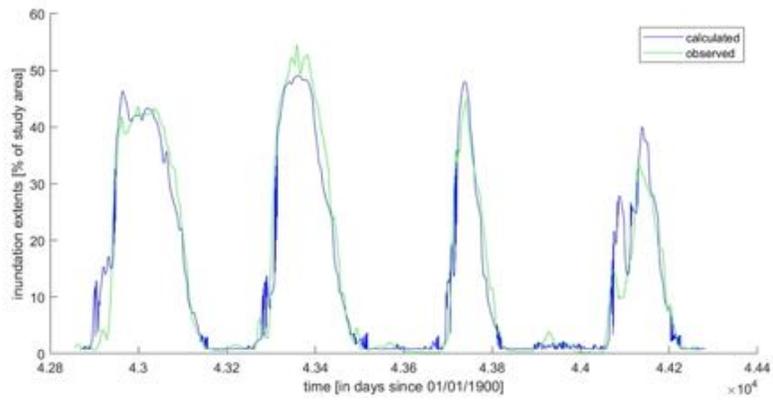


Figure 16: Observed inundation extents and extents calculated from upstream water levels using the Lamagat model, Zone A.

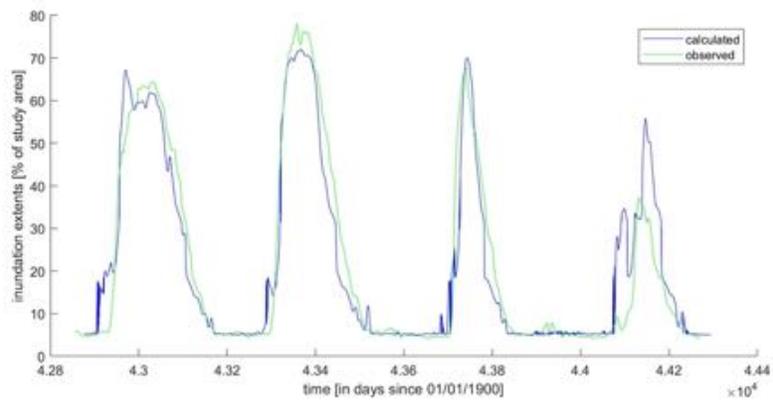


Figure 17: Observed inundation extents and extents calculated from upstream water levels using the Lamagat model, Zone B.

Water Level [m]	Optimal Delay Time
0.67	1
0.87	13.75
0.98	8.75
1.07	8.75
1.15	12.75
1.22	14.75
1.31	11.75
1.41	12.75
1.58	7.75
1.81	18.75
2.05	27.75
2.44	14.75
2.81	17.75
3.17	17.75
3.74	19.75
4.30	11.75
5.14	13.75
5.82	12.75
6.44	15.75

Table 4: Optimal correlation times by water level, Zone A

Water Level [m]	Optimal Delay Time
0.67	2.75
0.87	24.75
0.98	23.75
1.07	23.75
1.15	12.75
1.22	22.75
1.31	28.75
1.41	29.75
1.58	29.75
1.81	29.75
2.05	29.75
2.44	24.75
2.81	19.75
3.17	22.75
3.74	27.75
4.30	23.75
5.14	20.75
5.82	20.75
6.44	21.75

Table 5: Optimal correlation times by water level, Zone B

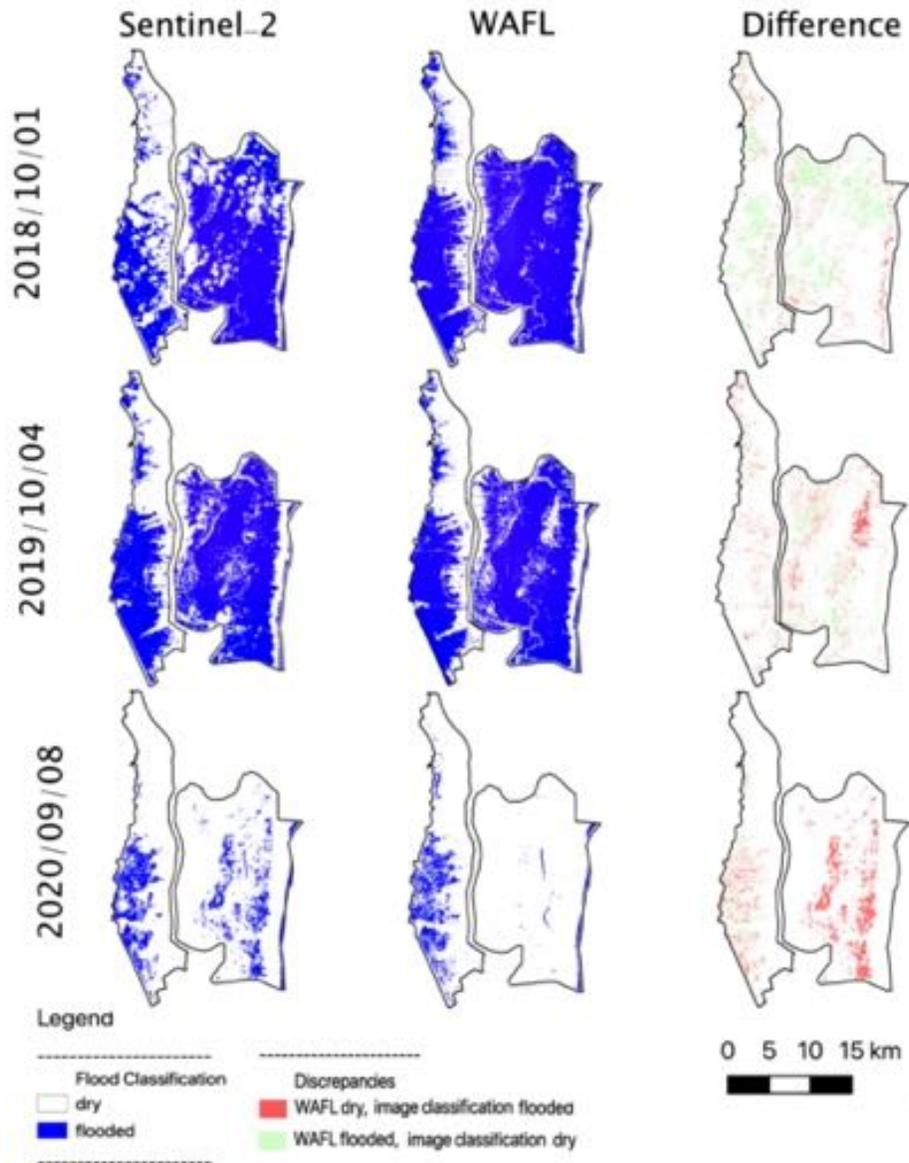


Figure 18: Comparison of WAFL-derived inundation extents, and extents directly derived from Sentinel-2 images in 2018, 2019, and 2020.

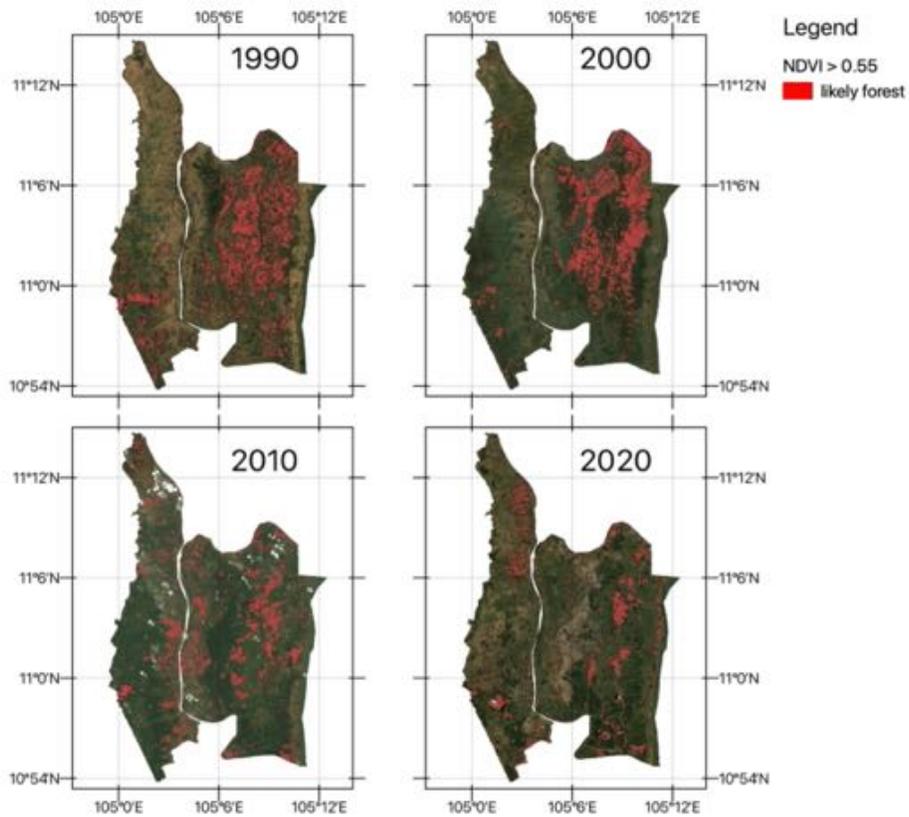
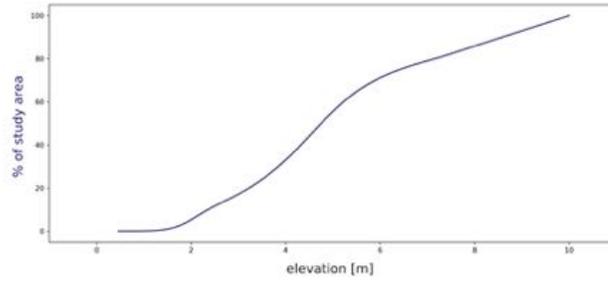
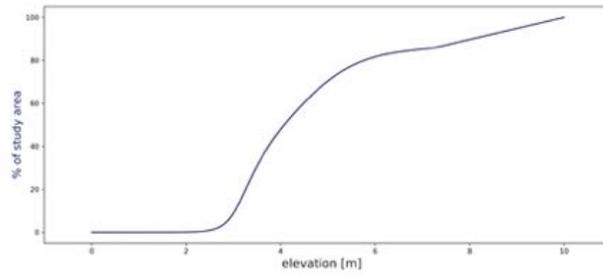


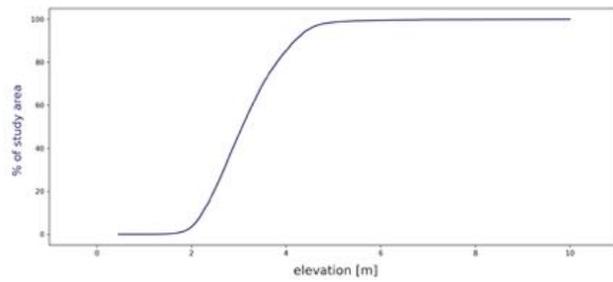
Figure 19: Distribution of natural vegetation in the early 1990s, 2000s, 2010s, and present.



(a) Elevation-area curve Zone A



(b) Elevation-area curve Zone B



(c) Elevation-area curve in the 1km-radius around the logger in Zone A

Figure 20: Elevation-area curves according to TanDEM

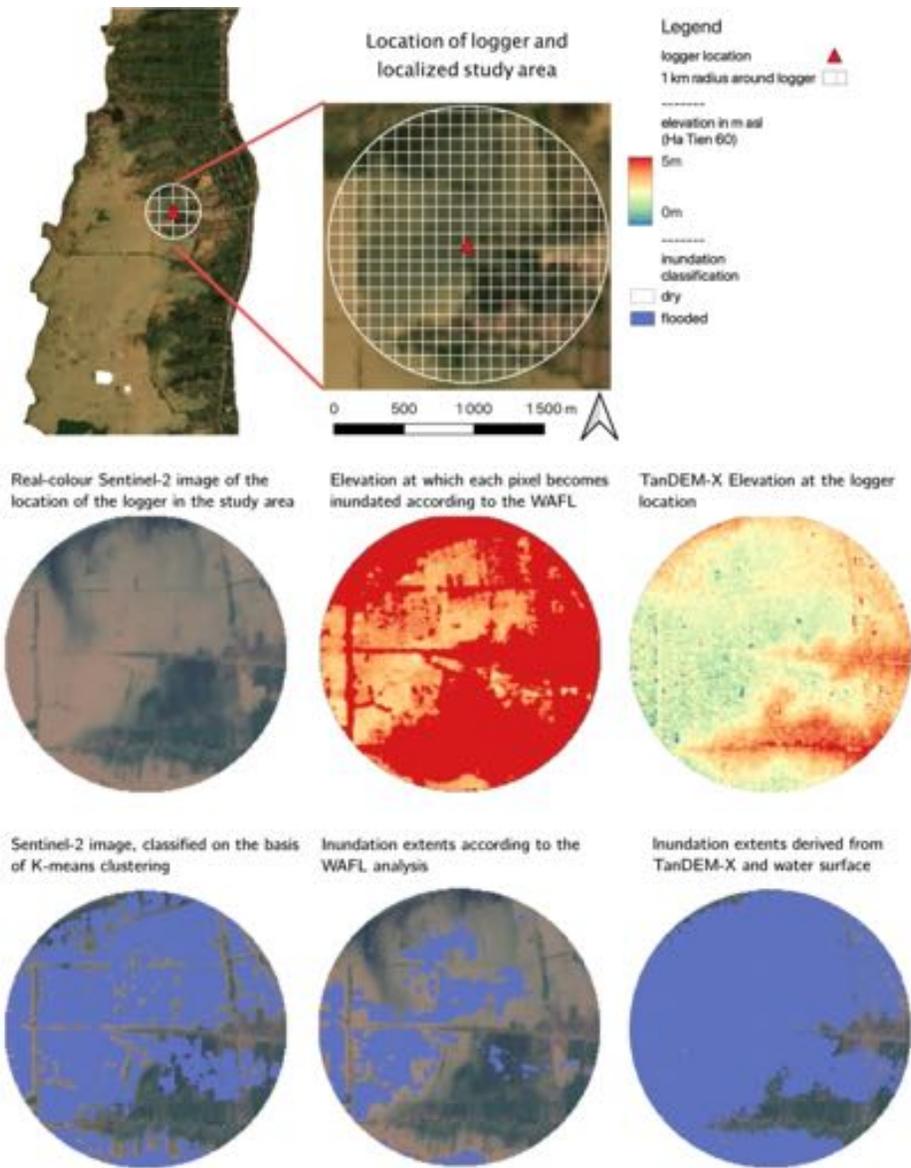
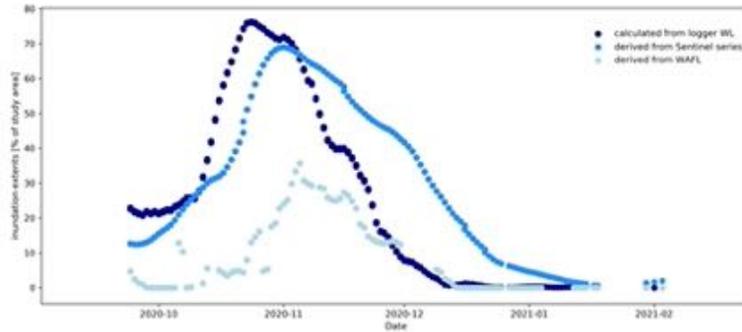
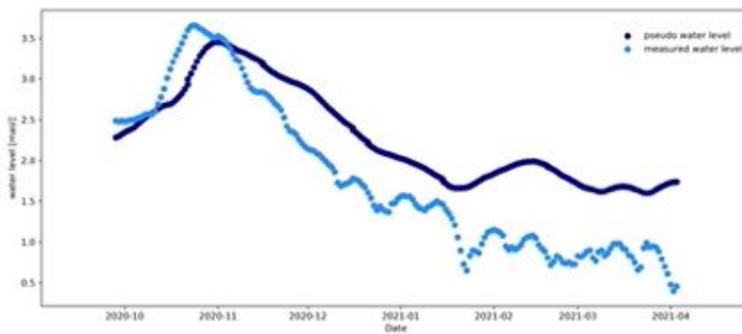


Figure 21: Local comparison of TanDEM-X-derived flood extent and WAFL-derived flood extent observed through Sentinel images.



(a) Percentage of flooded area in the 1 km radius around the in-situ logger at Prek Chann West (PCW), derived from Sentinel, and calculated via the elevation-area curve of the TanDEM-X and WAFL.



(b) Comparison of the pseudo-water-level calculated from the remote sensing observations and the TanDEM-X elevation-area curve, and the values measured by the in-situ logger

Figure 22: Comparison of DEM with local water level data.

1181 **Appendix G: Results of Analysis of Changes in Inundation Patterns**
1182 **in the Cambodian Mekong Delta**

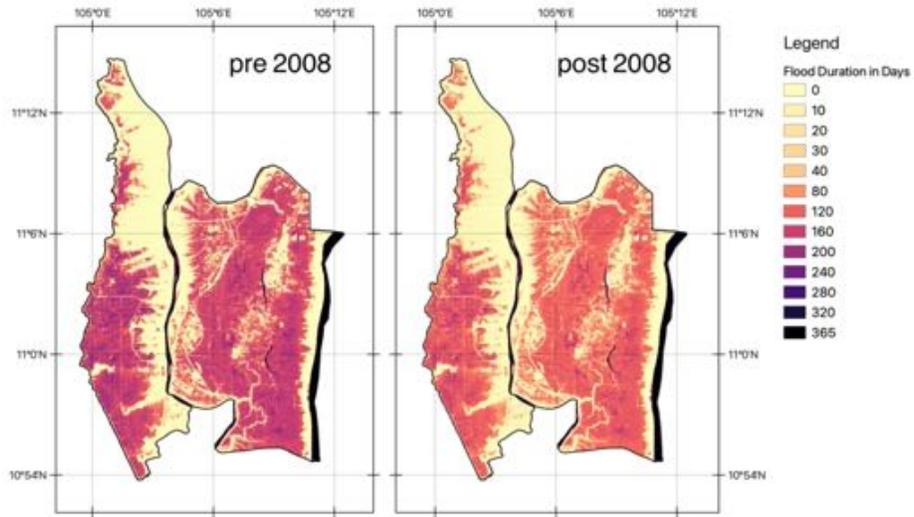


Figure 23: Change in inundation durations pre- and post-2008